The Impact of Natural Disasters on Neighborhood Change: Longitudinal Data Analysis

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SUMMARY

This dissertation seeks to explore the association between natural disasters and neighborhood change and further to examine the differential impact of natural disasters on neighborhood change according to the disaster itself, the rehabilitation efforts of local jurisdictions, and the characteristics of the affected neighborhoods.

Using the longitudinal model, it examines the shifts in neighborhood change trajectory before and after natural disaster for three indicators (home values, poverty rate and racial diversity). The results find that natural disasters have a significant impact on the trend of neighborhood change, reducing variation in the indicators within neighborhood. Home values and racial diversity of neighborhoods are likely to immediately decrease after natural disasters but not to shift in subsequent rate of change, while poverty rates are likely to instantly increase in the aftermath of the disasters and to annually decline over time.

This dissertation also explores the differential effects on neighborhood change according to intensity of natural disaster, neighborhoods' average income and the location. The results of the analyses are like the following: 1) the neighborhoods which the more intense disasters hit are more likely to experience the rapid decline in home values and an instant increase in their poverty rates than those which the less intense disaster hit. On the other hand, the more intense natural disasters are more likely to increase neighborhoods' racial diversity than the less intense natural disasters, while natural disasters themselves are likely to decrease it. 2) natural disasters might have the

more adverse impacts on low- and high-income neighborhoods than moderate-income neighborhoods and that the impacts on low-income neighborhoods are most severe. More importantly, the adverse impacts in low-income neighborhoods might be long lasting. 3) neighborhoods in suburban areas, compared to neighborhoods in the central cities, are likely to decrease in their home values after natural disasters and to increase in their poverty rates.

Finally, the findings of this dissertation confirms its main arguments that a natural disaster affects the trend of neighborhood change and intervenes in the path of change over time and that natural disasters differentially shift neighborhoods according to their characteristics. Further it suggests that these neighborhood changes, once accelerated by a natural disaster, further polarize residential populations on a metropolitan neighborhood scale.

CHAPTER 1
INTRODUCTION

Neighborhoods change over time. In general, neighborhood change is characterized as any significant change in the characteristics of a neighborhood over time. Changes are the result of activities such as moving-out, moving-in, incumbent upgrading, or property or neighborhood maintenance, which alter the number and composition of residents and subsequently the characteristics of a neighborhood. Many studies have attempted to explain both the underlying mechanisms through which neighborhood change is manifested and the larger context that governs why change occurs in distinct ways (i.e., Ellen and O'Regan 2008; Galster 2001; Grigsby et al. 1987; Rosenthal 2008; Temkin and Rohe 1996). Some explain neighborhood change as a result of the deterioration of housing stock in a particular neighborhood (i.e., filtering) (i.e., Ellen and O'Regan 2008; Grigsby et al. 1987; Rosenthal 2008). Some cite the social status of a neighborhood as a major cause of demographic transition (i.e., social externalities or invasion-succession) (i.e., Duncan and Duncan 1957; Rosenthal 2008; Vandell 1981). Others explain neighborhood change in terms of the complex relationships among economic and political institutions (i.e., Downs 1981; Stone 1993). Although researchers have reached no consensus about the key drivers that generate neighborhood change, they agree that neighborhoods change over time and that the pattern is not always continuous or linear, but often discontinuous or nonlinear (Galster et al. 2000, 2007; Guercia and Galster 2000).

The patterns of neighborhood change could be the result of natural disasters. Post-disaster case studies have suggested that natural disasters significantly change the aggregate characteristics of a neighborhood, including pushing specific groups out of the neighborhood and attracting others (Belcher and Bates 1983; Hunter 2005; Morrow-Jones and Morrow-Jones 1991). They believe that these neighborhood changes in the aftermath of natural disasters are substantially accelerated by two major factors: severe physical damage of property and an uneven recovery/reconstruction process. More importantly, the patterns of neighborhood change induced by disasters vary according to the characteristics of the affected neighborhoods. However, direct empirical evidence of a link between natural disasters and neighborhood change is scarce. The few empirical studies that have attempted to establish a link have found that natural disasters have a mixed impact on neighborhood change in the long-term. Nevertheless, they agree on two important points: First, the impact of natural disasters on neighborhood change is strongly associated with the intensity of a disaster; and second, a natural disaster does not equally affect all the neighborhoods of a stricken region.

These studies typically suffer from one or more methodological or conceptual shortcomings. First, the cases of natural disasters that studies have typically chosen are not optimal because they do not separate the impact of small-size disasters from that of larger-size ones even though they recognize the importance of the intensity of natural disasters to the impact on neighborhood change. Second, the studies tend not to deal with the differential effects stemming from either the number of natural disasters that have affected a neighborhood or the time lapse that has occurred since a disaster struck. Third, the studies often do not provide accurate counterfactuals that provide an appropriate baseline of comparison against which actual changes in the indicator of a neighborhood are measured to assess the putative impact of an intervention. More importantly, they may overlook an important fact that natural disasters are an intervention in the path of neighborhood change over time. This problem results from the use of traditional regression models that assume that observations are independent in terms of time. However, this assumption may be violated if a neighborhood changes over time, if the changes reflect a trend, if the natural disaster intervenes in the trend of the neighborhood change, and if the trend of the neighborhood change and the intervention effect of the natural disaster differ with regard to the characteristics of the neighborhood. These shortcomings limit the ability of researchers to draw definite conclusions about the nature of the link between natural disasters and neighborhood change.

This dissertation is an effort to link two traditional lines of research – natural hazards mitigation and neighborhood change – that have traditionally not been well connected. Neighborhood change literature has found that neighborhoods continue to change over time as a result of an interaction among various factors. When the historical trend of neighborhood change is interrupted by shocks from outside, the neighborhood changes differently from the way it changed in the past. Natural hazards literature, usually through case studies after natural disasters, has found that neighborhood characteristics change in the aftermath of a disaster. As a result, the neighborhoods shift from their historical trend of neighborhood change. This dissertation focuses on a natural disaster as one of main factors which may interrupt the trajectory of neighborhood change. The natural disaster that acts as an intervention in the normal time series of neighborhood change is considered as a connecting link between natural disaster literature and neighborhood change literature.

This dissertation seeks to examine community disaster resilience—its ability to absorb disaster impacts and rapidly return to normal socioeconomic activity (Lindell 2010)—at the neighborhood level in the long term. It investigates whether or not U.S. metropolitan neighborhoods are resilient to a natural disaster, by tracking a change in neighborhood trajectory after the natural disaster. In detail, the objective of this dissertation is to explore the association between natural disasters and neighborhood change and to examine the differential impact of natural disasters on neighborhood change according to the disaster itself, the rehabilitation efforts of local jurisdictions, and the characteristics of the affected neighborhoods.

To attain this objective, this dissertation seeks to answer following questions: (1) Does a natural disaster change the trend of neighborhood change?; (2) Does the impact of a natural disaster on neighborhood change differ according to the intensity of the disaster, the socioeconomic characteristics of the neighborhood, and the role of local municipalities in the metropolitan area to which the neighborhoods belong? (Are the neighborhoods that sustain more severe damage from a disaster more likely to change? Are lower-income neighborhoods more likely to experience an adverse change after a disaster? Are the neighborhoods located in larger municipalities more likely to experience growth and improvement than those in smaller ones?); and (3) Do natural disasters result in increasing disparity of populations on the neighborhood level?

This dissertation mainly argues that a natural disaster, as a "transient, exogenous shock (Galster et al. 2007)," affects the trend of neighborhood change and intervenes in the path of change over time. Physical damage and rehabilitation inputs following a natural disaster disrupt neighborhoods and then accelerate neighborhood change, prompting involved players to act. That is, a natural disaster above a specific size causes populations with specific socioeconomic characteristics to relocate from one neighborhood to another and then induces neighborhood change that begins in ways that are very different from those in the past. The dissertation also contends that these neighborhood changes, once accelerated by a natural disaster, further increase racial and income disparity of residential populations on a neighborhood scale. This increasing disparity among neighborhoods tends to increase significantly after a major natural disaster for two reasons. First, a pattern of relocation after a natural disaster varies according to socioeconomic or racial characteristics of a household (Dash et al. 1997; Frey and Singer 2006; Girard and Peacock 1997; Smith 1996; Smith and McCarty 1996). Such relocation patterns linked to socioeconomic and racial characteristics contribute to socioeconomic and racial disparity from neighborhood to neighborhood in the composition of a population: That is, while one specific socioeconomic group may leave for other neighborhoods with similar socioeconomic characteristics, other groups may stay in their neighborhood as groups with similar characteristics move in. Second, natural disasters affect neighborhood change differently according to a municipality's position within a regional stratification system, which has important consequences for the recovery process (Dash et al. 1997). The capacity of a local government to prompt and enable recovery exacerbates the disparity among neighborhoods due to the composition of the population, resulting in a different type of neighborhood change.

To test these hypotheses, this dissertation examines changes in the trends of metropolitan neighborhoods induced by five major hurricanes (Hurricane Allen of 1980; Hurricane Alicia of 1983; Hurricane Elena of 1985; Hurricane Gloria of 1985; Hurricane Hugo of 1989), all of which caused serious damage between 1980 and 1990. To efficiently estimate the effects of intervention following these natural disasters on neighborhood change, this study will examine, using the study period between 1970 and 2000, the trajectory of indicators of neighborhoods in the pre- and post-intervention periods. To carry out this analysis, it employs longitudinal models, "multilevel models for change," to examine the intervention effects of the hurricanes on neighborhood change (the level-1 model) and the differential effects according to the intensity of the hurricanes and the characteristics of the neighborhoods (the level-2 model). This model provides a more efficient estimation of the impact, both conceptually and methodologically, of the disasters.

This dissertation contributes to the existing literature in several ways. For one, it is the most comprehensive study examining the link between natural disasters and neighborhood change to date. Although other studies have examined this link, they suffer from several methodological and conceptual problems. To examine the effects of intervention following natural disasters on the changes in the characteristics of a neighborhood, this study uses superior statistical methodology: the longitudinal model. It also provides a thorough review of the empirical literature that examines the social and economic impact of natural disasters. Third, the study is the first to examine the impact of natural disasters on neighborhood change between 1970 and 2000. As already mentioned, finally, it is an effort to link the natural disaster literature to neighborhood change literature.

The organization of this dissertation follows. Chapter 2 presents an overview of the concept of a neighborhood and its change, the theoretical perspectives on the causes of neighborhood change over time, key outcomes of neighborhood change, and methods to measure neighborhood change induced by planned interventions. Following the overview is both an investigation of the existing literature in an effort to determine what previous studies have found pertaining to the connection between natural disasters and neighborhood change and an examination of empirical evidence for neighborhood change induced by natural disasters. Then, based on the literature review, Chapter 3 presents research questions and hypotheses about the impact of natural disasters on neighborhood change, and Chapter 4 proposes a research design for testing the research questions and hypotheses. Chapter 5 includes sections pertaining to the analyses and findings regarding the differential effects of natural disasters on neighborhood change. Chapter 6 concludes with critical findings and policy implications that can help planners and policy makers more effectively deal with the different change among neighborhoods after a natural disaster.

CHAPTER 2

LITERATURE REVIEW

This chapter examines the basic concept of a neighborhood and its change and discusses the underlying mechanisms through which neighborhood change is manifested. A review of the literature on the dynamics of neighborhood change can help us understand that neighborhoods change over time, even without natural disasters. Following this analysis is an investigation into the link between natural disasters and neighborhood change, which many post-disaster case studies have established. It reviews empirical studies on the impact of natural disasters on neighborhood change and discusses the limitations of the existing literature.

2.1. Dynamics of Neighborhood Change

It is widely recognized that over time, neighborhoods change through complex mechanisms. Here, as a background of neighborhood change, the concept of a neighborhood and the theoretical models of neighborhood change, which explain how neighborhoods change, are summarized. Then, several theoretical perspectives on the causes of neighborhood change are discussed, the key outcomes of neighborhood change that many studies on neighborhoods have primarily dealt with are presented, and methodologies to measure neighborhood change caused by planned interventions such as welfare policies are described and critiqued. Understanding the dynamics of neighborhood change and methods of tracking neighborhood change trajectory helps us to efficiently estimate the impact of natural disasters on neighborhood change because disasters, like planned interventions, affect changes in the characteristics of neighborhoods by intervening in the underlying mechanisms of neighborhood change.

2.1.1 Background of Neighborhood Change

2.1.1.1. Concept of a Neighborhood

Despite the long history of interest in urban neighborhoods, researchers have not reached a consensus about precisely what they are or what they should be. Some have employed an ecological perspective. For example, Keller (1968) defined a neighborhood as a "place with physical and symbolic boundaries" (p. 89). Morris and Hess (1975) labeled it as a "place and people, with the common sense limit as the area one can easily work over" (p. 6). Golab (1982) used the phrase "a physical or geographical entity with specific (subjective) boundaries" (p. 72) to define a neighborhood. Others have attempted to integrate social and ecological perspectives. Hallman (1984) considered a neighborhood "a limited territory within a larger urban area, where people inhabit dwellings and interact socially" (p. 13). Warren (1981) defined it as "a social organization of a population residing in a geographically proximate locale" (p. 62). Downs (1981, p. 15) defined it as "geographic units within which certain social relationships exist." Schoenberg (1979) specified the defining characteristics of a neighborhood as "common named boundaries, more than one institution identified with the area, and more than one tie of shared public space or social network" (p. 69). However, the same scholars often do not explicitly define "neighborhood" when investigating neighborhood change.

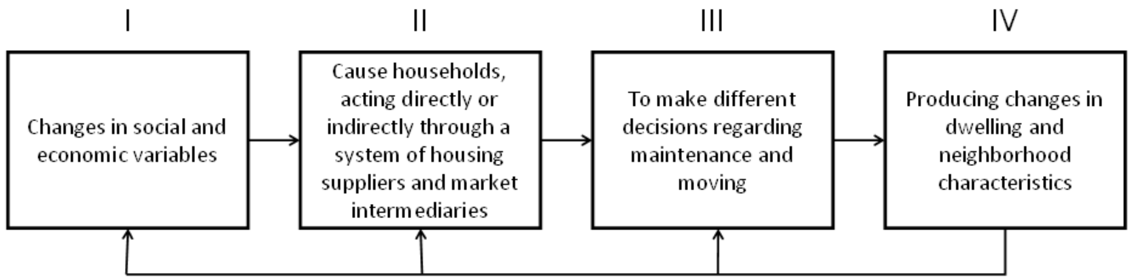
Galster (2001) pointed out that all of these definitions suffer from common shortcomings: They consider either a certain degree of spatial extent or social interrelationships within that space but tend to underplay many other features of the local residential environment that clearly affect its quality from the perspective of residents, property owners, and investors. Instead, he defined a neighborhood as a "complex commodity" produced by the same players—households, businesses, property owners, and local governments—that consume them. According to him, a neighborhood is a bundle of spatially-based attributes, including a structural, infrastructural, demographic, class status, tax/public service package, with particular environmental, proxemic, political, social-interactive, and sentimental characteristics. Thus, neighborhoods are more likely to be viewed as physical and social environments that affect the lives of their inhabitants for better or worse.

In this context, researchers have tried to delineate neighborhoods, some by using the pattern of interaction among residents (Festinger et al. 1950) and others by constructing spatial neighborhoods from the perception of residents (Jacobs 1961; Lynch 1960). Sawicki and Flynn (1996) identified two critical factors at issue when determining how to delineate neighborhoods: "the permanency of boundaries, coupled with the availability of data" and "the idea of the neighborhood as an appropriate context for studying human behavior and social action" (p.176). Several researchers have employed the census tract as a proxy of a neighborhood to conduct cross-sectional analyses of cities and their neighborhoods (e.g., Galster and Mincy 1993; Jargowsky 1997, 2003; Kasarda 1993). Examining poverty concentration in the central cities, for example, Wilson (1987) and Sessoms and Wolch (2008) used tracts to define neighborhoods in Chicago and Los Angeles, respectively. These tracts, available from the Census Bureau for each decade, include an average of about 4,000 people and are the smallest unit of analysis for the most reliable, detailed social and economic data on households, people, and housing as well as physical data on housing. Census tracts also provide relatively constant boundaries so that change over time can be measured more accurately. Thus, most studies, in an effort to track neighborhood change, have defined neighborhoods as tracts (e.g., Ellen and O'Regan 2008; Galster et al. 2003; Rosenthal 2008; Swanstrom et al. 2008). However, they must also recognize that tracts do not always match local residents' perceptions of their neighborhoods as functioning social areas (Sawicki and Flynn 1996).

2.1.1.2. Models of Neighborhood Change

In general, neighborhood change is considered as any significant shift in the characteristics of a neighborhood over time. The literature is replete with neighborhood change models such as McKenzie's (1925) invasion-succession theory and Hoover and Vernon's (1959) life-cycle theory, which primarily include ecological perspectives that view neighborhood change as a natural phenomenon. The invasion-succession theory explains neighborhood change through a major mechanism by which natural areas change. The terms "invasion" and "succession," borrowed from plant and animal ecology, were used to describe the processes of the alternation of neighborhood populations. In particular, Duncan and Duncan (1957) indentified four basic stages for the process of neighborhood change: penetration, invasion, consolidation, and piling up. The authors, however, argued that neighborhoods need not pass through all of the stages and that different neighborhoods may pass through these stages at different rates. Hoover and Vernon (1959) argued that many neighborhoods of the city undergo a process of life-cycle change that involves five stages: development, transition, downgrading, thinning out, and renewal. According to this model, as a neighborhood passes from one stage to the next, several characteristics of the neighborhood change: the racial and age composition of the population, the density of the population, and the quality and condition of housing. Downs (1981) pointed out that "the diversity of life cycles means that, within a single city, neighborhoods in a variety of stages can exist simultaneously" (p. 69). These ecological perspectives on neighborhood change, however, have been criticized from the political economy perspective by many researchers. In particular, Metzger (2000) challenged the neighborhood life-cycle theory, arguing that it undermined the political mechanism under which neighborhoods change. In his view, neighborhood change, especially neighborhood decline, is the result of disinvestment that stems from "power games" that developers, realtors, lenders and appraisers play.

Grigsby et al. (1987) provided an integrated model that fully captures the social and economic variables that drive neighborhood change, the actions and decisions of agents in light of these changing variables, and the changes they bring out in dwelling and neighborhood characteristics (Megbolugbe et al. 1996). They conceptually identified a process of neighborhood change, the framework of which is illustrated in Figure 2.1. According to the process, a change in any one of a number of social or economic variables reacting to the systems of housing suppliers and market intermediaries causes households to make different maintenance and moving decisions, which ultimately alter the characteristics of residential structures and their neighborhoods. These alterations may, in turn, feed back to social or economic variables, intermediate variables, or household decisions, causing secondary changes in neighborhood characteristics.



Source: Grigsby et al. 1987, p. 31

Figure 2-1. Framework for the Process of Neighborhood Change

This process focuses on the actions of key players such as households, developers, and public agencies affected by the social or economic variables inside or outside of a neighborhood and the direct and indirect changes prompted by these actions in dwelling and neighborhood characteristics. Most importantly, it deals with interactions among social and economic variables as initial causes of neighborhood change and indicators of neighborhood change as effects of the changed social and economic variables. Interactions are the driving force for continuous neighborhood change. That is, although all neighborhoods undergo chronological change, they do so in varying degrees.

Recent research showed that the pattern of neighborhood change is not always continuous or linear but often discontinuous or nonlinear (Galster et al. 2000, 2007; Quercia and Galster 2000). Galster and his colleague characterized this discontinuous or nonlinear pattern of neighborhood change as threshold effects, defined as “a dynamic process in which the magnitude of the response changes significantly as the triggering stimulus exceeds some critical value" (p. 146). That is, when neighborhoods are upset by "transient, exogenous shock," the drivers of neighborhood change inside or outside of a neighborhood, the neighborhood responds differently from the way it responded in the past.

2.1.2. Theoretical Perspectives on the Causes of Neighborhood Change

Many studies have attempted to explain both the mechanisms through which neighborhood change is manifested and the larger context that governs why it occurs in distinct ways (Downs 1981; Ellen and O'Regan 2008; Galster 2001; Grigsby et al. 1987; Rosenthal 2008; Temkin and Rohe 1996). They commonly recognize that neighborhood change results from the interaction among a variety of factors in the neighborhood at both local and regional levels. In particular, Grigsby et al. (1987) identified most of the factors that we now consider the causes of neighborhood change. The factors are grouped into both exogenous (i.e., demographic and economic changes, government intervention, and obsolescence) and endogenous (i.e., positive or negative externalities and changing expectations) to the neighborhood. They viewed these forces as linked. Of these factors, several theories, which mainly filtering, externalities (invasion-succession), and political economy, discuss the key drivers of neighborhood change (Schwirian 1983; Temkin and Rohe 1996). The theories are not mutually exclusive, but instead, interrelated in the process of neighborhood change (Temkin and Rohe 1996).

The first theory follows from the filtering model, which explains the process of neighborhood change according to the ages and the level of deterioration of residential structures (e.g., Lowry 1960; Muth 1972). The theory posits that as the housing of a neighborhood ages and deteriorates, higher-income residents move out of the neighborhood, opting for newer neighborhoods with more modern housing; then low-income households occupy their old housing. As much of the housing stock ages and deteriorates in the older neighborhood, it eventually begins to fall out of the market entirely and becomes a target for redevelopment. Grigsby et al. (1987) explained the change in the composition of residents in a neighborhood through the filtering process, introducing the concept of "neighborhood succession," defined as "a shift in the income profile of occupants of a geographically defined neighborhood of dwelling units" (p. 27). They asserted that the quality and the age of the dwelling units significantly contribute to a shift in an absolute or relative position on the income scale of neighborhoods. Furthermore, using housing submarkets, Rothenberg et al. (1991) applied the model of housing dynamics to neighborhood dynamics. From their perspective, neighborhood change closely relates to the dynamics of the metropolitan housing submarket, indicating that inter-neighborhood flow toward "household upgrading" results in neighborhood transition.

In this filtering model, the quality of dwelling units in a neighborhood plays a significant role in any change that takes place in neighborhood indicators. In particular, the filtering model considers the age of the housing stock a key driver of neighborhood change. In recent research pertaining to change in the economic status of neighborhood, Rosenthal (2008) found that compared to new and old housing, the presence of middle-aged homes reduces the degree to which a neighborhood may raise its economic status and that the presence of old housing is "a forerunner to urban redevelopment and gentrification" (p. 834). Ellen and O'Regan (2008) also showed that the presence of new homes in a neighborhood is significantly associated with a positive change in the average household income in a neighborhood.

The second theory, based on the theory of "invasion-succession," focuses on social externalities. Duncan and Duncan (1957) explained neighborhood racial transition through an invasion-succession model. In their view, a change from white to black in racially-mixed neighborhoods is inevitable. Once blacks penetrate a neighborhood inhabited exclusively by whites, the number and the proportion of blacks in a neighborhood continuously increase while those of whites continuously decrease until a complete turnover in the population from white to black occupancy takes place. Closely related to the invasion-succession model, Schelling (1971) introduced the tipping model, indicating that households may choose to migrate into or out of a neighborhood based on the socio-demographic characteristics of their prospective neighbors, and then small changes in the demographic composition of a neighborhood can lead to the rapid tipping of the neighborhood from one group to another. Therefore, neighborhood externalities contribute to migration and related change in the characteristics of a neighborhood. Rosenthal (2008) explained such neighborhood externalities in two ways. First, certain types of families may behave in ways that generate either social capital or costs for the neighborhood, influencing the decision of other families to migrate. Second, families may choose to migrate into or out of a neighborhood based on the socio-demographic characteristics of their prospective neighbors.

These externality models suggest that the social and economic status of the neighborhood is a key driver of neighborhood change and that it can be measured by socioeconomic factors, including homeownership, average income, and the racial/ethnic composition of the neighborhood (e.g., Ellen and O'Regan 2008; Rosenthal 2008). The results of empirical research on neighborhood change indicate that these socioeconomic factors that provide social externalities have important effects on neighborhood change. For example, a higher rate of homeownership in a neighborhood causes the economic status of the neighborhood to rise, indicating that homeowners provide social capital because they are more likely to belong or volunteer their time to neighborhood groups (DiPasquale and Glaeser 1999). However, some researchers have noted that these neighborhood demographic and socioeconomic attributes have different effects according to the economic status of a neighborhood (Ellen and O'Regan 2008; Galster et al. 2003).

The final family of theories, the political economy group, seeks to explain neighborhood change in terms of the complex relationship among economic and political institutions and the various segments of the housing market (Schwirian 1983). According to these theories, powerful elites who are key players use urban space to facilitate capital accumulation, resulting in a change in the characteristics of neighborhoods. Effectively representing the notion of neighborhood change caused by these economic and political institutions are the "growth machines" posited by Molotch (1976). That is, the wealth of a neighborhood depends on the relationship between the use and exchange values of the neighborhood, and the contradiction between theses values is often resolved in favor of capital interests (Logan and Molotch 1987). Furthermore, political economists believe that the fate of any neighborhood is determined by not only the major players in a neighborhood, but also the economic, political, and social forces outside its boundaries (e.g., Downs 1981; Stone 1993). The fate of neighborhoods in a city changes as the social, economic, and political climate changes. As a result, the city experiences an uneven distribution in the benefits of development and revitalization.

Neighborhood political economy theory covers a broad range of theories, including the theories of discrimination, such as disparate treatment and impact, redlining, and disinvestment. Challenging traditional urban theory, which explains the fate of neighborhoods in terms of residential mobility, some researchers have argued that historical and structural discrimination in the residential real estate and mortgage markets are a major impetus of change in the characteristics of neighborhoods. In reality, real estate agents and lenders discriminate against minority customers, specifically black and Hispanic renters and homebuyers, because of racial prejudices, financial resources, and related issues (Schwartz 2006). Mortgage lenders often do not provide loans to people within particular geographic areas ("redlining"), nor do they divulge information to whites about the diversity of neighborhoods as they do for other racial groups. In addition, they often encourage whites to consider more predominantly white neighborhoods (i.e.,"geographic steering") (e.g., Turner and Ross 2005; Yinger 1995). Moreover, while white borrowers and communities rely mostly on lower-cost conventional mortgages, black and Hispanic borrowers and communities are less likely to receive conventional mortgages and more likely to take out subprime or government-insured mortgages (e.g., Apgar and Calder 2005; Bradford 2002; Immergluck 2004). Discrimination stemming from changes in the racial composition of neighborhoods tends to sustain residential segregation and inequality (Turner and Ross 2005) and the subsequent concentrated poverty (Massey and Denton 1988, 1993; Massey and Egger 1990). It is also responsibility for rising foreclosure rates, which in turn differentially affect vacancy rates, change in the black population, and the housing tenure status of residents (Baxter and Lauria 2000). Finally, structural discrimination in the housing market affects the entire process of neighborhood change.

Other political economy researchers have argued that neighborhood change, especially suburban neighborhood decline and inner-city neighborhood revitalization, results from the circulation of capital in the built environment and the policy regime through a systemic disinvestment-reinvestment process (e.g., Newman and Ashton 2004; Pitkin 2004; Smith et al. 2001; Stone 1993). Neighborhood disinvestment can be triggered two processes: discrimination and uneven development (Bradford and Rubinowitz 1975; Pitkin 2004; Smith et al. 2001). Discrimination in housing and credit markets leads to disinvestment in specific neighborhoods in terms of the denial of capital (e.g., Pitkin 2004). Uneven development is a structural process of built environment dynamics in a metropolitan area through the movement of capital in terms of reinvestment following disinvestment (e.g., Bradford and Rubinowitz 1975). On the neighborhood level, the role of the state in creating the conditions for disinvestment-reinvestment cycles has been acknowledged (e.g., Listokin and Wyly 2000; Newman and Ashton 2004; Smith 2002). Recently, urban policies and regulations pertaining to neighborhood revitalization through gentrification and deconcentrating poverty have fostered the redevelopment of inner-urban neighborhoods that had been structurally disinvested in during the last four decades (Newman and Ashton 2004).

In this context, the key drivers of neighborhood change within the framework of the political economy model are neighborhood attributes, which are more likely to enhance the exchange use of a neighborhood. These attributes work for major factor to facilitate the maximization of profit and capital accumulation in the process of discrimination and in the conditions of disinvestment-reinvestment cycles. A typical example is the location of a neighborhood such as proximity to a highway or central location inside a metropolitan area.

The findings from the literature on the underlying mechanisms of neighborhood change indicate that neighborhoods continue to change stemming from a number of drivers both inside and outside of neighborhoods, and some households seek to move out, opting for newer and better-quality housing units. Some households leave their neighborhoods, searching for neighborhoods with a specific socioeconomic or racial composition. In addition, some households move either into or out of neighborhoods that have been redeveloped in the pursuit of profits. An important point is that the characteristics of neighborhoods change as a result of these underlying mechanisms, even without any other interventions such as natural disasters.

2.1.3. Key Outcomes of Neighborhood Change

Many researchers have studied neighborhood change patterns over time. Research has encompassed a variety of neighborhood change patterns, including changes in economic status or racial composition, the concentration of poverty in the central city, the decline of inner-suburban neighborhoods, gentrification, and neighborhood revitalization induced by subsidized public programs. The literature has provided evidence that a variety of types of neighborhood changes such as those pertaining to income, unemployment, poverty, welfare, and the structural characteristics of property can be references in the examination of neighborhood change. Although one type of outcome cannot sufficiently represent neighborhood change, the literature shows that the most commonly studied outcomes of neighborhood change are those pertaining to economic status, housing stock quality, and racial and income diversity. While shifts in economic status and diversity imply the societal transformation of a neighborhood, improvement or deterioration in the quality of houses in the neighborhood indicates a change in the physical quality of the neighborhood.

2.1.3.1. Changes in Economic Status

An important finding of analyses of neighborhood change is the outcome of economic status. To examine the outcomes of neighborhood economic status in a neighborhood, researchers have employed income or poverty level (Galster and Mincy 1993; Galster et al. 2003). In their investigations, researchers have tracked the trajectory of the income or the poverty level of neighborhoods with a slightly different focus on the pattern of neighborhood change. Some researchers have focused on shifts in the wealth of poor neighborhoods, tracking changes in the incomes of households or families over several decades (e.g., Ellen and O'Regan 2008; Galster et al. 2003; Rosenthal 2008). Others have employed the poverty level to measure certain patterns of neighborhood change such as the gentrification and the decline of inner-suburban neighborhoods (e.g., Bostic and Martin 2003; Lucy and Phillips 2000; McKinnish et al. 2007).

Research on neighborhood economic change has dealt with the shifts in the wealth of urban low-income neighborhoods. Galster and his colleagues (Galster and Mincy 1993; Galster et al. 2003) employed the poverty rate to measure a change in the economic status of low-income neighborhoods in U.S. metropolitan areas. The change in the poverty level of low-income neighborhoods, defined as those with 20% or higher poverty rates, is mainly determined by regional economic cycles and population growth, which shown that neighborhoods with higher poverty rates are less likely to be stable (Galster et al. 2003). Recent research, however, on low-income neighborhood change has focused on income as an indicator of neighborhood change. For example, Zielenbach (2005) examined quantitative changes in Chicago's low-income community areas from 1990 to 2000. The study focused principally on neighborhoods with per capita incomes at or below 80 percent of the citywide per capita income in 1990. To explore the differences in neighborhood conditions, the author grouped community areas into four clusters based on income trends, immigration patterns, and racial composition. The results of the study showed that in general, demographically and geographically similar communities changed in similar ways but not necessarily at similar rates or to the same extent. Rosenthal (2008) studied the dynamics of neighborhood change in 35 metropolitan areas in the U.S. over several decades and found substantial movement. He defined four quintiles of neighborhood types (i.e., low-income, lower-middle income, upper-middle income, and high-income neighborhoods), based on the ratio of average household income in a neighborhood to the average household income in the metropolitan area. He found that roughly two-thirds of the census tracts that were low-income in 1950 had climbed into a higher income category by 2000. Ellen and O'Regan (2008) offered new empirical evidence about the prospects of lower-income U.S. urban neighborhoods during the 1990s. In addition to capturing neighborhood economic status, they utilized a relative measure of income: the ratio of average household income in the tract to that in the metropolitan area. To measure economic gain or improvement, neighborhoods that experienced a positive increase in their relative income during any given decade were identified as gaining economically in that decade, and neighborhoods that experienced a ten percentage-point increase in their relative income in a decade were considered to have experienced a large economic gain. They found a significant shift in the wealth of lower-income urban neighborhoods during the 1990s, which witnessed a notable increase in the proportion of lower-income and poor neighborhoods experiencing a gain in economic status.

Researchers have also used the outcomes of economic status to examine specific patterns of neighborhood change such as gentrification and the decline of inner-suburban neighborhoods. Most research on gentrification has used increases in income and changes in the poverty rate as one of several indicators that measure the extent of gentrification of a neighborhood (e.g., Galster and Peacock 1986; Wyly and Hammel 1998). In particular, some studies have measured the gentrification of a neighborhood solely by using a change in the income of the neighborhood (Bostic and Martin 2003; McKinnish et al. 2007). Bostic and Martin (2003), identifying gentrifying neighborhoods, defined a neighborhood as gentrifiable if its median income was less than 50 percent of the median income for the MSA. Then, they designated a neighborhood as gentrifying if its classification switched from gentrifiable to non-gentrifiable during the period of analysis. Using income to study the demographic process underlying the gentrification of low-income urban neighborhoods, McKinnish et al. (2007) also identified gentrification ring the 1990s. They labeled gentrifying neighborhoods as census tracts in the low-income neighborhood sample that experienced an increase in average family income of at least $10,000 between 1990 and 2000.

Analyzing the transformation of the inner suburbs in U.S. metropolitan areas, researchers have tried to identify the decline of inner suburban neighborhoods by investigating changes in the economic status of households or families, such as changes in income and the poverty level (Hanlon and Vicino 2007; Lucy and Phillips 2000; Orfield 2002). These studies are essential to the examination of neighborhood change because suburban decline has a similar flavor in which similar socioeconomic measures of neighborhood decay are applicable. In particular, Lucy and Phillips (2000), in their study of 554 suburbs in 24 states, referred to suburban decline as income decline, focusing on median family income in a local jurisdiction relative to metropolitan trends. Hanlon and Vicino (2007) identified the decline of inner suburbs in Baltimore between 1980 and 2000, examining changes in median family income and the poverty rates in these neighborhoods.

2.1.3.2. Changes in the Quality of the Housing Stock

Researchers consider a shift in the quality of housing stock in a neighborhood as an important outcome when tracking neighborhood change (e.g., Bier 2001; Margulis 2002; Freeman 2005; Anacker & Morrow-Jones 2008; Ellen et al. 2001). They have mainly focused on the values of housing units to measure the quality of housing units because housing units are fixed in space and their prices reflect the characteristics of their surroundings as well as the characteristics of the unit and competing options. Housing units are not directly influenced by the characteristics of in-movers and out-movers per se. They are durable, and they do not change easily, so they are a more stable measure. As an increase or a decrease in property values in a neighborhood indicates improvement or deterioration in the physical quality of the neighborhood, property values, measured primarily by the sales prices of housing units, have been used to examine neighborhood change patterns such as gentrification, neighborhood decline, and neighborhood change induced by revitalization programs.

One strong measure of neighborhood improvement is a change in the property values resulting gentrification. Galster and Peacock (1986) noted the criterion of specified real property values as important for measuring gentrification, ascertaining whether the operational definition of gentrification has an impact on the apparent extent, the location, and other causal factors associated with the phenomenon. Examining the association between gentrification and dislocation, Freeman (2005) also considered an increase in housing prices together with changes in occupation and education level of residents as indicators of a gentrifying neighborhood. According to Freeman, one criterion that can be used to distinguish the level of gentrification in one neighborhood from that of other neighborhoods is reinvestment, so he used housing prices as a proxy for investment after gentrification. That is, he believed that an increase in housing prices in a gentrified neighborhood was the result of an increase in investment in the neighborhood after gentrification.

From another perspective, Anacker and Morrow-Jones (2008) used property values to measure neighborhood deterioration. In particular, they analyzed the decline in suburban neighborhoods in the Cleveland area by examining changes in the property values of single-family homes in declining suburbs, comparing them with those in the central city and developing suburbs. In addition, they analyzed specific factors that may have influenced the property values of single-family homes. They argued that if suburban neighborhoods in which many of these homeowners lived suffered problems or decline, the value of property would decrease and loss of investment value would follow.

Many studies on the impact of revitalization programs on distressed neighborhoods have also utilized property values to estimate neighborhood change, particularly neighborhood revitalization after the implementation of government welfare programs (e.g., Ellen et al. 2001; Galster et al. 2006; Schwartz et al. 2006). For example, Ellen et al. (2001) examined the impact of two New York City homeownership programs on the revitalization of surrounding neighborhoods. The programs subsidized the construction of affordable owner-occupied homes in distressed neighborhoods. Specifically, they compared the prices of properties in small rings surrounding government subsidized sites with the prices of comparable properties in the same ZIP code but outside the ring. Then they examined whether the magnitude of this difference in property values changed after the completion of the homeownership development. Galster et al. (2006) assessed the impact of a revitalization program on targeted neighborhoods by measuring the pattern of neighborhood change using single-family home prices. They specifically investigated the change in trajectories of the target neighborhoods from what they would have been in the absence of intervention and a nonlinear relationship between home prices and dollars invested in individual blocks in impact areas.

Property values, specifically the sales price of property, have been used to examine shifts in the physical characteristics of a neighborhood. In general, an increase in property values in a neighborhood indicates neighborhood improvement, especially revitalization or gentrification in distressed neighborhoods, while a decrease in the values indicates neighborhood deterioration, which the literature has illustrated in the decline of inner-suburban neighborhoods. More importantly, the literature on the impact of revitalization programs on neighborhood change shows that the trends of changes in neighborhood indicators should be examined if neighborhood change is to be efficiently measured.

2.1.3.3. Changes in Racial and Income Diversity

Neighborhood diversity is a key element to the understanding of how neighborhoods change over time. In general, research has dealt with neighborhood diversity, linking it with segregation among various income or racial groups in a neighborhood. Such research has examined and measured economic or racial segregation in myriad ways such as those that use poverty concentration, relative diversity (or segregation) indices, or absolute diversity measures.

Since the 1980s, researchers have shed light on segregation based on income on the neighborhood level, particularly the concentration of poverty in central U.S. cities, and employed poverty rates to measure the segregation of income (e.g., Jargowsky 1997, 2003; Kasarda 1993; Kingsley and Pettit 2003; Wilson 1987). To explain geographically concentrated poverty and the subsequent development of a ghetto underclass, Wilson (1987) pointed to the exodus of middle- and working-class black families from many inner-city ghetto neighborhoods. He was the first to employ the 40 percent criterion in his empirical analysis of poverty concentration within Chicago's urban neighborhoods during the 1970s. He defined poverty areas, high-poverty areas, and extreme-poverty areas as census tracts with a poverty rate of at least 20 percent, 30 percent, and 40 percent, respectively. He then counted the number of areas that met these criteria and found an extraordinary increase in both poor and non-poor populations in extreme-poverty areas between 1970 and 1980.

Following Wilson, scholars frequently endorsed the use of the 40 percent threshold to denote poverty concentration within urban areas. In particular, Jargowsky (1997) examined the association between concentrated poverty and neighborhood sorting, which determines how segregated households of different incomes are from one another. He defined the neighborhood poverty rate as the percentage of the population that resides in high-poverty neighborhoods and measured economic segregation levels using the ratio of the neighborhood-income standard deviation to the household-income standard deviation. He concluded that "the overall level of economic segregation helps explain ghetto poverty levels in 1990, and the changes in economic segregation among blacks—Wilson's 'flight of the black middle class'—play a role in the changes in ghetto poverty between 1980 and 1990" (p. 183).

In an attempt to explain the causes of concentrated poverty, Massey and his colleagues focused on variation in the degree of poverty concentration among racial groups (Massey and Denton 1988, 1993; Massey and Eggers 1990). They introduced methods of measuring neighborhood diversity, focusing on the key diversity (or segregation) indices: the exposure index and the dissimilarity index. They offered a benchmark of how to measure segregation and hypersegregation. Massey and Eggers (1990) examined trends in the geographic concentration of poverty among whites, blacks, Hispanics, and Asians in 60 U.S. metropolitan areas from 1970 to 1980. In this study, the authors sought to measure both the concentration of poverty by using single summary statistics and the propensity of middle-class minorities to live apart from their poor counterparts. In their analysis, they employed the *exposure* index (*P**), which determines the likelihood of residential contact between or among income groups. *P** represents the relative probability that members of any two income groups in a metropolitan area will share the same census tract; it provides a simple measure of the degree to which classes are physically exposed to one another by virtue of sharing a tract. A number of researchers (e.g., Abramson et al. 1995; Holloway et al. 1999; Strait 2006) have used this index as a measure of poverty concentration, race segregation, and racial diversity.

Another diversity (or segregation) index, the dissimilarity index, measures the evenness of the distribution of any specific group in a metropolitan area. Specifically, the dissimilarity index indicates the percentage of members in a particular group (e.g., the poor or blacks) that would have to move from one neighborhood to another to achieve an even distribution of group members throughout a metropolitan area, the number of persons moving expressed as a proportion of the number that would have to move under conditions of maximum segregation (Massy and Denton 1988). Massey and Denton (1988) measured the segregation of three minority groups from non-Hispanic whites in 60 metropolitan areas. Abramson et al. (1999) used the index to measure the segregation of the poor in 100 U.S. metropolitan areas in 1970, 1980, and 1990. Such studies have shown that while blacks still retain a peculiar segregation pattern, neighborhoods are generally changing toward a more integrated racial-ethnic and diverse structure (Hou and Milan 2003).

Some researchers, however, have criticized that these relative measures of diversity have shortcomings (Ellen 1998; Galster 1998; Immergluck and Smith 2003). The proportion of a certain racial or socioeconomic group in a neighborhood can signal various meaning of diversity for those in a metropolitan area that the neighborhood belongs to. This variation is linked to the limits of "cross-sectional or intertemporal comparability" (Galster 1998 p.44) because the racial or income composition of the metropolitan area varies across space or time. Instead of the relative measure, they employed an absolute measure of diversity that categories neighborhoods according to a predetermined range of racial or income composition and tracks a change in the categories for a neighborhood across time.

Examining racial integration in neighborhoods in 34 US metropolitan areas, Ellen (1998) identified three neighborhood categories according to the proportion of black population in a neighborhood; predominantly white, integrated, and predominantly black. She measured racial change in a neighborhood over a ten-year period, examining increases and decreases in the proportion of the white population. She defined neighborhoods with a decrease and increase or an increase of at least ten percentage points in the white population as "succession" and "displacement" neighborhoods, respectively, while referring to other neighborhoods as "stable." Immergluck and Smith (2003) measured neighborhood diversity by examining the extent of racial and income segregation among homebuyers. They defined five categories of neighborhood income diversity, based on a proportion of homebuyers with low or moderate income. For racial diversity, they defined seven categories according to the proportions of whites, blacks and Hispanics in a neighborhood. Shifts in the proportions over a particular time period were investigated to measure changes in neighborhood diversity.

Recently, a large number of studies on income inequality and economic segregation have employed the entropy index, an absolute measure of diversity (Fischer 2003;

Fischer et al. 2004; Fong and Shibuya 2000; Galster et al. 2008; Talen 2006). The index is based on the proportion of a certain group in a neighborhood. For instance, Fong and Shibuya (2000) examined the extent of spatial separation of the poor in Canadian cities and measured the level of economic segregation within a group by the entropy index. Talen (2006), using census tracts in Chicago, employed the index to measure income diversity based on census-reported income groups. Galster et al. (2008) also used the index to explore income diversity within neighborhoods in the 100 largest metropolitan areas in the United States and to measure the diversity of six income groups. The entropy index has several advantages over other measures of diversity: First, it can easily compare more than two groups at a time, incorporating the diversity levels of more than two groups into a single index (Fischer 2003; Fong and Shibuya 2000); second, it can "decompose into independent and dependent contributions of different constituent variables, such as race and class" (Fischer 2003, p. 675). Thus, Reardon and Firebaugh (2002) concluded that the entropy index is superior to other measures, such as the exposure or dissimilarity indices.

2.1.4. Measures of Neighborhood Change Induced by Planned Interventions

A large body of literature has considered the impact of planned interventions on neighborhoods (e.g., Brown 2009; Ellen et al. 2001; Galster et al. 2004, 2006; Schwartz et al. 2006; Smith 2003; Zielenbach 2003). Planned interventions include a variety of government projects or programs, such as neighborhood revitalization programs (e.g., HOPE VI) and subsidized housing programs (e.g., Low Income Housing Tax Credit (LIHTC) and Section 8 for tenants). Studies have applied various approaches to investigate how the planned interventions affect not only neighborhood in which the interventions occur but also surrounding neighborhoods.

One common approach for detecting the impact of the interventions in neighborhoods, referred to as the "post-intervention, relative-change approach" (Galster et al. 2004, 2006) is to compare the outcomes of neighborhood change during or after the intervention period to the outcomes in similar neighborhoods that do not have the intervention. Zielenbach (2003) used this approach to analyze economic changes in HOPE VI neighborhoods, comparing these changes not only to changes in other high-poverty neighborhoods within the respective cities but also to overall trends in the cities. They assumed that HOPE VI neighborhoods and other high-poverty neighborhoods had the same characteristics before the HOPE VI intervention (Freeman and Botein 2002), indicating that any difference between target neighborhood change and control neighborhood changes could be attributable to this specific intervention. However, without the examination of the other variables, we cannot determine whether the two neighborhoods were truly comparable (Freeman and Botein 2002; Galster et al. 2004, 2006; Schwartz et al. 2006).

Another approach for discerning the impacts of intervention on neighborhoods is to combine the test/control and pre/post methods, referred to as the "difference-in-differences approach," which involves measuring the difference between the patterns of neighborhood change of target and control neighborhoods and then examining changes in the magnitude of this difference before and after the intervention. For example, Ellen et al. (2001) investigated the impact of affordable homeownership programs in New York City. They estimated the difference between the change in property values near new owner-occupied homes before and after completion and the value appreciation of properties outside the ring but still in the same neighborhood. The approach assumes that change in the differences between target and control neighborhoods before and after intervention is the result of intervention. However, this approach may lead to erroneous conclusions if observations establishing indicator slopes are insufficient (i.e., the trends of an outcome indicator between target and control neighborhoods) both before and after an intervention (Galster et al. 2004). Comparisons of levels before and after an intervention may make identifying pre- and post-intervention difference in slopes difficult.

Pointing out the methodological challenges of identifying and measuring the influences of an intervention on neighborhood change, Galster and his colleagues (2004) developed the Adjusted Interrupted Time Series (AITS) model, which estimates "the slopes and levels of the indicator in both the target and control areas both before and after the intervention, adjusting the former as appropriate for changes in the latter to establish the counterfactual situation" (p.154). The strength of this approach is that it establishes a convincing counterfactual to which actual changes in target areas can be compared, allowing us to plausibly deduce causation (Galster et al. 2006). It does so by extrapolating the pre-intervention trend in the outcome indicator of the target neighborhoods into the post-intervention period.

This approach was utilized to evaluate the impact of community development initiatives such as HOPE VI (Brown 2009; Galster et al. 2004, 2006). The basic AITS regression models include a set of dummy and slope variables that indicate the location and the time of sale of properties located in target and control neighborhoods. For example, one study presents the level of a target neighborhood by a dummy variable denoting that a sale occurred in one of the target areas. The level of a target neighborhood in the post-intervention period is characterized by dummy variable denoting that a sale occurred in one of the target areas during the post-intervention period, the purpose of which is to test whether or not “a discontinuous, time-invariant change” in the home price levels in the impact neighborhood occurred after the intervention. A trend occurring in a target neighborhood is demonstrated by slope variables for home values in target areas both pre- and post-intervention.[1] The trend occurring the target neighborhood after the intervention is represented by a slope variable for home prices in target areas post-intervention,[2] the purpose of which is to test that whether or not a change in the price-time slopes has occurred in the target areas. The coefficient of the variable provides the “(time-dependent) magnitude of impact.”

2.2. The Link Between a Natural Disaster and Neighborhood Change

2.2.1. Neighborhood Change in the Response to a Natural Disaster

Many researchers have argued the importance of land use planning and management to mitigate natural hazards. In particular, Nelson and French (2002) find that communities with high-quality land use plans experienced significantly less property damages from the earthquake. In floodplain cases, some research provides empirical findings that land use planning and management have positive effects on regulating the extent of floodplain development (Burby & Dalton, 1994; Burby & French, 1985) and

[1] The value is “1” if a sale occurred in the target areas during the first year of the study period, “2” if a sale occurred in the target areas during the second year, and so on.
[2] The value is “1” if a sale occurred in the target areas during the first year of the intervention period, “2” if a sale occurred in the target areas during the second year, and so on.

finally on decreasing vulnerability to floods. Recognizing the importance of institutional aspect in natural hazard mitigation, some natural hazard researchers have emphasized on the role of state mandates, which encourage local governments to adopt land use planning (Burby & Dalton, 1994). Burby and Dalton (1994) claim that local governments' land use plans can be an effective tool of restricting development in the environmentally sensitive areas and the state or federal government's mandate can lead the local governments to adopt such land use plans. Although land use planning plays a significant role in mitigation natural hazards, local governments often are reluctant to adopt the plans (Burby, 2006; Burby & French, 1981; Burby, French et al., 1985). Burby (2006) explains it, using the idea of "local government paradox," which means "that while their citizens bear the brunt of human suffering and financial loss in disasters, local officials pay insufficient attention to policies to limit vulnerability (p.171)."

As a result, natural disasters often cause extensive damage to personal property and the infrastructure of an area, which contributes to the widespread displacement of a population and limits the ability of evacuees to return to their homes, businesses, and neighborhoods. The hazard literature has shown that the relocation of households forced out by natural disasters separates families and further disrupts or changes neighborhoods from what they were in the past (e.g., Dash et al. 1997; Frey and Singer 2006; Girard and Peacock 1997; Smith and McCarty 1996).

Several theoretical perspectives on migration provide foundations upon which we can examine the association between neighborhood change and natural disasters. From their viewpoints, natural disasters can represent not only a "push" factor but also a "pull" factor in a decision by a household to move out of or into a neighborhood. On the one hand, natural disasters might act as a "push" factor, causing households to move out of their neighborhoods (Belcher and Bates 1983; Hunter 2005; Morrow-Jones and Morrow-Jones 1991). Such forced migration takes the form of evacuation, which is typically temporary. However, for many disaster-impacted residents, natural disasters become a catalyst for permanent migration, particularly by those seeking to achieve previously held aspirations. On the other hand, because the reconstruction process that follows a natural disaster often provides economic opportunities that have not presented themselves before the event (Belcher and Bates 1983; Pais and Elliot 2008), the natural disaster might play a role as a "pull" factor responsible for new households' moving into a neighborhood affected by a natural disaster. This interplay between the "push" and "pull" factors in the aftermath of a natural disaster is directly responsible for a substantial redistribution of the population, promoting movement of a specific population into or out of neighborhoods and resulting in further changes in the aggregate characteristics of neighborhoods.

One of main reasons that we should focus on neighborhood change caused by a natural disaster is that the disaster generally has a negative impact on not only neighborhoods themselves but also the economy in the surrounding areas. Exploring the determinants of business recovery after the 1994 Northridge earthquake, Dalhamer and Tierney (1998) found that severely damaged businesses have difficulties returning to their prior status. Extensive commercial and residential disruption in the surrounding neighborhoods may limit businesses' ability to recover even for those that did not suffer direct physical damages.

After a natural disaster strikes a neighborhood, altering the underlying mechanism in the larger context, the neighborhood changes because of the direct impact of the natural disaster and the recovery and reconstruction processes. Many post-disaster case studies have shown that the physical damage to personal property from disaster and the uneven recovery/reconstruction process result in changes in the composition of residents in a neighborhood.

2.2.1.1. Direct Impact of a Natural Disaster

Most population movements and reconstruction processes in the aftermath of natural disasters take place in areas where the event has caused the most physical damage. The destruction of homes in neighborhoods almost certainly brings about a displacement of residents (Belcher and Bates 1983; Elliott and Pais 2006; Landry et al. 2007; Pais and Elliott 2008; Paxon and Rouse 2008; Smith and McCarty 1996). In addition, severely damaged neighborhoods are more likely to undergo a transformation of their built environment in the process of reconstruction and recovery than other neighborhoods (Dash et al. 2007; Pais and Elliott 2008). Therefore, the extent of physical damage in a neighborhood contributes to the degree of not only the migration (in- and out-migration) but also to the transformation of its built environment. Overall, changes in both the residents and the built environment lead to considerable change in the neighborhood.

Through a case study on the impact of the Northridge earthquake, Bolin and Stanford (1998b) demonstrated the process of neighborhood change following the ensuing damage and destruction to property. After the earthquake, the residents left in great numbers, abandoning the housing units in the most heavily damaged neighborhoods and adjacent neighborhoods of Los Angeles. While most of these neighborhoods have since been rebuilt, during the recovery period, the neighborhoods themselves were transformed owing to significant shifts in resident populations. In some neighborhoods, former residents belonging to specific ethnic groups left the area, and migrants from elsewhere in the city replaced them. After the earthquake, a significant restructuring of homeownership, business ownership, and ethnic composition in these neighborhoods characterized the recovery process. Given the dynamic shifts in the ethnic composition of the neighborhoods across Los Angeles, such transformations were expected, and in this case, accelerated by earthquake-related population shifts of displaced households.

Several studies on the impact of Hurricane Katrina on migration show a significant relationship between physical damage and population movement (Frey and Singer 2006; Landry et al. 2007; Paxson and Rouse 2008). The areas of the Gulf Coast impacted by Hurricane Katrina sustained both population gains and losses. In particular, the New Orleans metropolitan area, which sustained the greatest amount of physical damage, experienced the biggest losses in population (Frey and Singer 2006). After all, the households that experienced serious damage were the most likely to leave their neighborhoods after the hurricane and the least likely to return (Landry et al. 2007; Paxson and Rouse 2008). These findings imply that the more serious damage a neighborhood sustains, the more vulnerable to change it is.

More importantly, natural disaster researchers have observed social variation in relocation patterns after natural disasters (Dash et al. 1997; Girard and Peacock 1997; Landry et al. 2007). They note that the variation in relocation patterns is strongly associated with the degree of vulnerability to disasters. Vulnerability is defined as "the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist and recover from the impact of a hazard" (Hunter 2005, p. 283). Not surprisingly, most vulnerable individuals or groups are at the low end of the socio-economic spectrum.

Social variation in vulnerability is important with regard to the social context of natural disasters (Blaikie et al. 1994; Cutter et al. 2003; Girard and Peacock 1997). In particular Cutter and her colleagues, using a factor analysis, explored the factors that influence the social vulnerability to environmental hazards. They found that low-income families, women and minorities including black are more vulnerable to hazards and that they were slower to absorb and recover from losses.

Morrow-Jones and Morrow-Jones (1991), using Annual Housing Survey data from 1974 through 1981, empirically tested social vulnerability to natural disasters. Examining the distinct differences between the socioeconomic characteristics of disaster movers and those of other forced movers, they found that the less powerful, such as the poor, the elderly, and minorities, move in disproportionate numbers after a natural disaster, compared to other forced movers. Recent analyses of the wind damage and flooding caused by Hurricane Katrina also found that the impact of the storm was disproportionately borne by the African American Community, by people who rented their homes, and by the poor and unemployed (Logan 2006; Muro et al. 2005).

Many case studies after major natural disasters have produced similar results of social vulnerability in the patterns of displacement and relocation. Research on the impact of Hurricane Andrew indicated that socioeconomic status is associated with migration in Southern Florida, where low-income households are more likely to reside in highly vulnerable mobile homes and less likely to have invested in disaster mitigation (Peacock and Girard 1997). For example, they are more likely to have insufficient insurance, so they often receive insufficient or no settlements for rebuilding (Peacock and Girard 1997). A comparison between the pre- and post-Hurricane Katrina population compositions in New Orleans showed that while many low-income households comprising, moved out of the New Orleans metropolitan area as a result of the hurricane, higher-income households, made up of whites, were less likely to leave (Frey and Singer, 2006). Research on the likelihood of returning to New Orleans indicated that individuals or households who were renters or blacks were less likely to return to their pre-Katrina homes (Elliott and Pais 2006; Fussell et al. 2009; Landry et al. 2007; Paxson and Rouse 2008). In particular, race disparities in return rates were largely accounted for by differences in the housing damage experienced by blacks and whites (Fussell et al. 2009). These findings imply that the socioeconomic characteristics or the race of households is critical to the decision to move out of neighborhoods after a natural disaster. The neighborhoods struck by natural disasters are more likely to experience changes in socioeconomic and racial/ethnic composition. More importantly, recognizing the way that socioeconomic status or race has been spatially institutionalized in the urban environment is key to the understanding of trends in neighborhood change after natural disasters.

Recently, Zhang and Peacock (2010) examined the changes in housing recovery trajectories after Hurricane Andrew. They found that an increase in hurricane damage resulted in a drop in home values and the negative effects attenuated over time. However, damaged homes take much longer than two years to return to pre-disaster values. In particular, black and low-income neighborhoods experienced higher losses in home value compared to white and high-income neighborhoods and take more time to return to the prior status. While sales and abandonments occurred in neighborhoods with heavier damage, abandonments were more concentrated in lower income and minority neighborhoods. These results suggest that the physical damage from a natural disaster can cause a change in the characteristics of a neighborhood and that such neighborhood changes differ according to the characteristics of neighborhoods.

2.2.1.2. Recovery and Reconstruction Processes

The processes of recovery and reconstruction in the aftermath of a natural disaster take place within a larger social and political context (Bolin and Stanford 1998b; Kamel and Loukaitou-Sideris 2004; Hartman and Squires 2006; Peacock et al. 1997; Quarantelli 1999). That is, both processes reflect the dynamic nature of social and political processes on all spatial scales. Examining the recovery process of historical major natural disasters, Powers (2006) concluded that "the degree of suffering experienced by people recovering from disaster is inversely correlated with the actions of the government or relief agency to protect them from market forces" (pp.28-29). A key to understanding such processes in both social and political contexts requires an awareness of the polarized nature of the recovery process, evidenced in the inequitable access to government assistance by various ethnic and socioeconomic groups (Kamel and Loukaitou-Sideris 2004). Post-disaster recovery processes are recognized not simply as discriminatory practices in the distribution of assistance, but rather as design processes that "reproduce a particular social order and rely on definitions of social justice that are tailored to the ruling interests" (Kamel and Loukaitou-Sideris 2004, p.536). This inequitable access to recovery funds from governments is strongly associated with the various relocation patterns of households and the diverse change patterns across neighborhoods, according to their socioeconomic status. It also reproduces a spatial institutionalization of social disparity in an urban environment. Natural disaster researchers have attributed these differences in relocation and neighborhood change patterns in the recovery and reconstruction processes to factors: the socioeconomic characteristics of households or neighborhoods and the importance of a municipality within the metropolitan area.

First, the socioeconomic status of a family or a neighborhood plays a strong role in the recovery process and its outcome. Disaster scholars have documented that in the aftermath of a disaster, the socially marginalized, such as the poor, minorities, single-parent households (which are mostly female), and the elderly, are more likely to suffer from "unmet recovery needs" than other groups and subsequently to end up worse off than they were prior to the disaster (Bolin and Stanford 1998a 1998b; Fothergill and Peek 2004; Loukaitou-Sideris and Kamel 2004; Peacock et al. 1997; Quarantelli 1999). After a natural disaster, people or households on a low socioeconomic status (SES) are more likely to experience severe economic hardship because they have less financial and/or economic capital at the time of the crisis (Chappell et al. 2007). Thus, they are more likely to depend on government disaster aid. Nevertheless, they have generally had limited access to government aid because they are less comfortable negotiating with bureaucrats for disaster relief assistance (Fothergill 2004), less knowledgeable about the system of recovery and sources of financial aid (Fothergill and Peek 2004), and less participative in decision-making, and less accessible to external resources (Morrow and Peacock 1997). Without special assistance, homeowners unable to afford repairs or to arrange financing for their rehabilitation are more likely to experience demolition of their homes (Comerio et al. 1994; Bolin and Stanford 1998b). Thus, these people or households experience a more serious degree of suffering during the process of recovery from a disaster. Indeed, the lower the socioeconomic level of a family is, the less likely the family will recover to their pre-impact level. It is understood that “variations in recovery outcomes are a function of the level of vulnerability of particular social groups, such as low-income and ethnic minorities” (Kamel and Loukaitou-Sideris 2004, p.538). Typically, in the aftermath of a disaster, the situation of an already economically-stressed neighborhood composed of residents of a low socioeconomic status is more likely to be exacerbated by the polarized recovery process (Bolin 1986).

Taylor and Silver (2006) focused on the critical role of financial institutions in the recovery and reconstruction of New Orleans regions struck by Hurricane Katrina. After the hurricane, most of the approved disaster-related home loans went to families in affluent communities while a small portion went to families residing in poor neighborhoods. According to the authors, the approval patterns reflected the patter of “redlining”, which is historically related to unequal access to market-rate loans for gulf region residents. They claimed that if inequalities were not dramatically reduced, especially among minority and lower-income residents, neighborhoods composed of such residents would suffer from substantially more loss and roadblock during the recovery and reconstruction processes, indicating in the New Orleans region, minority and low-income neighborhoods will continue to suffer more in the aftermath of natural disasters in the relatively long-term compared than their white and higher-income counterparts. This phenomenon will likely result in an accelerated deterioration of the physical environment in these neighborhoods, which can alter the trends of neighborhood change.

Kamel and Loukaitou-Sideris (2004) empirically validated this polarized recovery process and its outcomes, examining the effects of the distribution of assistance on the outcome of long-term recovery from the Northridge Earthquake. They found that the distribution of federal assistance and consequently the potential for recovery from the earthquake was strongly associated with the particular socio-demographic characteristics of households and neighborhoods. Wealthier homeowners and neighborhoods with a large stock of single-family housing had more access to federal programs and resources than poor neighborhoods with higher concentrations of rentals and multifamily apartment buildings. In other words, wealthy and poor neighborhoods that sustained similar levels of damage did not receive similar levels of assistance, so they ultimately experienced different recovery outcomes. The neighborhoods that received less assistance relative to the reported damage experienced a net loss in population, a reduction in the number of housing units, and a lower occupancy rate. Finally, the authors concluded that the structural constraints of the existing recovery programs led to the 'marginalization of the marginalized' (Peacock and Girard 1997).

In addition to socioeconomic characteristics, the relative importance of a municipality within a metropolitan area affects the recovery outcomes of its households and neighborhoods after a major disaster. The local government of a large municipality can use its newfound resources and power through aggressive expansion by increasing its local population with newcomers and the number of housing units during the time of recovery. However, smaller, weaker local governments within stratified urban ecological networks can be both a result and a cause of continuing class and racial segregation. This variation in recovery outcomes among municipalities as far as which receives a larger share of federal assistance is strongly related to the level of power they wield and action they take. In the United States, "variations in the distribution of federal assistance across municipalities can depend on the political importance of local officials and their ability to mobilise interest in Washington" (Kamel and Loukaitou-Sideris 2004, p.537). Researchers have found that the size and the density of a population and the degree of urbanization are essential contexts within which to view the processes of recovery and reconstruction (Cross 2001; Passerini 2000; US General Accounting Ofice 1995). After all, large municipalities have larger at-risk populations, but they also may have greatest resources and abilities to deal with disasters: On the other hand, small municipalities have far smaller at-risk populations but a higher proportion of vulnerable populations (Cross 2001). The impact of a natural disaster can be severe over an entire smaller municipality because of a lag in relief efforts and external assistance and a lack of capacity to recover (Passerini 2000; US General Accounting Office 1995). Variations in the response capacities of municipalities profoundly influence the long-term consequences of a natural disaster on individual households and their neighborhoods.

The findings of post-disaster case studies confirm the significant role a municipality plays in the recovery outcomes of its residents and neighborhoods. Bolin and Stanford (1998b) observed that municipalities affected by the Northridge earthquake displayed discrepant abilities in acquiring and using federal assistance. Local authorities in large municipalities such as Los Angeles received public resources of funding from state and federal governments and used them to establish broader development projects such as the construction of roads, the renewal of older neighborhoods and other development projects that had no connection to the effects of the natural disaster. As a result, the municipalities were more likely to experience increases in the number of newcomers as well as out-migrants from the renewed old neighborhoods (Pais and Elliott 2008). On the other hand, Dash et al. (1997) found that after Hurricane Andrew, in a very small, predominantly black incorporated municipality, the proportion of the black population increased while that of the white population declined; in contrast, in a large, predominantly white municipality, the proportions of the two groups did not change. Bolin and Stanford (1998a) also found that political and economic conditions produced differential outcomes in the recovery and reconstruction processes after the Northridge earthquake in two California municipalities. The poor rural municipality was forced to construct low-income housing units to tide the residents over during a regional affordable housing crisis because the municipality lacked an entrenched Anglo power structure. In addition, the racial disparity in neighborhoods can increase because of a weakened capacity of a local government to direct a recovery program. These findings indicate that after a natural disaster, neighborhoods change in diverse ways according to the local jurisdictions to which the neighborhoods belong.

2.2.2. Empirical Evidence: The Long-Term Impact on Neighborhood Change

Although several scholars have examined the long-range consequences of natural disasters in particular communities, in general, they have not presented a clear picture of their overall effects. Disasters may have clear positive effects (Dacy and Kunreuther 1969) or clear negative effects, at least for some elements of the stricken population (Cochrane 1975; Haas, Kates, and Bowden 1977). Thus, they could either promote or accelerate pre-disaster trends occurring affected communities (Bates et al. 1963; Haas, Kates, and Bowden 1977) or result in no discernible long-term effects (Friesema et al. 1979). Dash et al. (2007) noted changes in the composition of one community in Miami-Dade County in the aftermath of Hurricane Andrew. The community hit by the hurricane experienced "Hispanicization," or a relative increase in Hispanics and blacks moving into the neighborhood and whites moving out, unlike Miami-Dade County as a whole. Their study also found that many of the households in the community were still suffering ten years later. However, the study did not look at the impact of the disaster on any isolated segment of a community such as a neighborhood but instead it focused on the community, or the county, as a whole.

Very few empirical studies have examined the impact of natural disasters on neighborhood change. Among these studies, just two studies conducted by Wright et al. (1979) and Pais and Elliott (2008), who used the census tract as a unit of analysis, shed light on the long-term effects of natural disasters on neighborhoods. However, these studies dealt with different types of natural disasters during different periods. Wright et al. examined neighborhood changes induced by three different types of natural disasters between 1960 and 1970, and Pais and Elliott explored neighborhood changes in three different zones according to the magnitude of three major hurricanes between 1990 and 2000.

Wright et al. (1979) conducted analyses of the long-term effects of all the major floods, tornadoes, and hurricanes that occurred between 1960 and 1970. They investigated changes in the total population and the total number of housing units in all the census tracts in standard metropolitan statistical areas (SMSAs) that experienced a major disaster along with all the tracts in a control sample of metropolitan areas that did not experience disasters. In their study, neighborhoods hit by disasters were defined as tracts within areas affected by the disasters that triggered a response from either the Red Cross, the SBA, or the federal government. These disasters included small- and middle-size disasters as well as extreme disasters. They examined the present characteristics of a neighborhood hit by a natural disaster as function of three primary sets of variables: the past characteristics of the neighborhood; the past characteristics of the SMSA where the neighborhood was located; and the intensity of the major disaster. The general model that they employed could be stated as follows:

$$TractCharacteristic_i^{1970} = \beta_1 + \beta_2 TractCharacteristic_i^{1960} + \beta_3 SMSA_i^{1960} + \beta_4 Disaster_i + e$$

The results of these analyses showed that natural disasters had a positive impact on both the populations and housing units, but the impact was not statistically significant. That is, natural disasters occurring in neighborhoods exacted no discernible effects that materially altered either population or housing growth trends between 1960 and 1970. The authors explained the lack of effects in two ways: First, impacted neighborhoods are effectively restored within ten years; second, the positive effects on neighborhoods seem to be offset by the negative effects in other neighborhoods, producing no effect in the aggregate. This argument was supported by another interesting finding—that high-income neighborhoods (approximately the upper third of families at the median-income level) appear to be favorably affected by floods while low-income neighborhoods are likely to be adversely affected. This finding indicates that while the higher-income neighborhoods had significantly higher growth rates in population and housing units than would be expected because of their other characteristics, the lower-income neighborhoods experienced some difficulty restoring themselves in the aftermath of floods. Wright et al. noted that "census tracts contain a lot of people, property and capital. The comparison of average damages to average resources makes it implausible in the extreme to expect that these disasters would have residual and observable effects. In our studies, none were found" (p. 198). Thus, they concluded that although they are serious events, not all natural disasters overwhelm the capacities of the areas involved.

Yezer and Rubin (1987), however, suggested that the effects of natural disasters depend on prior expectations regarding disaster rates. If disasters occur at anticipated rates, they will not affect the allocation of resources (including labor); if they occur at higher than anticipated rates, they will reduce productivity and utility, spurring the out-migration of both capital and labor. Therefore, it is possible that natural disasters with largely unexpected magnitude and intensity have a significant long-range impact on the affected neighborhoods. This argument is supported by Pais and Elliott (2008), who examined changes in neighborhood characteristics after three major hurricanes to understand how social inequality conditions one's exposure to environmental disasters and how such inequality repeats itself in the recovery process. Using census tracts as primary units of analysis, the authors combined data from the 1990 (pre-storm) and 2000 (post-storm) censuses with data from the Hazards U.S. Multi-Hazard (HAZUS-MH)[3] software, which provides an estimate of hurricane intensities across affected regions. While Wright et al. (1979) used binominal variables to determine whether or not a tract had been hit by a natural disaster during the study period, Pais and Elliott divided the regions affected by the hurricanes into three zones for each region (i.e., the recovery core, the inner ring, and the outer ring) according to the intensity of the hurricane winds. Then they compared the changes that took place in the neighborhood characteristics (i.e., total

[3] The Hazards U.S. Multi-Hazard (HAZUS-MH) is a nationally applicable standardized methodology and software program that estimates potential losses from earthquakes, hurricane winds, and floods, all on the geographic level of census tracts. The HAZUS-MH was developed by the Federal Emergency Agency (FEMA). The historical modeling function of HAZUS provides information about the intensities of historical major natural disasters for census tracts.

population, housing units, median household income, median home values, race, age, and homeownership) of the three zones and estimated the characteristics (e.g., population change) of each zone separately following the general model below:

$$TractCharacteristic_i^{2000} = \beta_1 + \beta_2 TractCharacteristic_i^{1990} + \beta_3 WindZone_i + \beta_4 Coastal_i + e.$$

The findings can be summarized in two ways. First, regions grew substantially after major hurricanes, and second, this growth tended to be spatially uneven. The neighborhoods in the core recovery zone that sustained serious damage by the major hurricanes became smaller, whiter, and older during the recovery process. In contrast, the surrounding neighborhoods in the inner ring of the recovery zone grew dramatically, fueled by expanding black and Latino/immigrant populations and by households with declining incomes relative to the rest of the affected region. These findings, based on various types of neighborhood characteristics, probe the effects of hurricanes themselves and recovery in the aftermath.

The results of both studies provide evidence that natural disasters have a mixed impact on neighborhood change, especially on the growth of populations and housing units in the long-term. However, they agree that the effects strongly depend on the intensity of the events: While an average intensity natural disaster has no discernible effects on neighborhood change, a large-scale disaster affects neighborhood change positively. Another important contribution of these studies is that "whatever effects there are from natural disasters, they are probably not shouldered equally by all neighborhoods of the stricken community" (Wright et al. 1979, p. 43). The changes that take place in high-income neighborhoods differ from those that occur in low-income neighborhoods; that is, while high-income neighborhoods grow and improve, low-income neighborhoods decline. In addition, neighborhoods that are more strongly affected by disasters undergo migration patterns that differ from those in surrounding neighborhoods. Thus, the keys to greater awareness of the long-term impact of neighborhoods are the accurate identification of the intensity of the natural disasters and the stratification of neighborhoods according to key factors that have a significant impact on recovery outcomes in the aftermath of the natural disasters.

2.2.3. Limitations of the Existing Literature

Although the two empirical studies that estimated the long-term impact of natural disasters on neighborhood change revealed several important findings, neighborhood-level effects reflect some methodological and conceptual problems, four of which deserve special mention.

First, the cases of natural disasters chosen by the two studies are inherently flawed. Wright et al. (1979) chose all the natural disasters that had occurred during the study period, but all varied in severity. They sought to analyze the effects of small- and medium-sized disasters as well as the effects of very large-scale disasters, but they did not separate the effects of smaller disasters from larger ones. Thus, they were not able to predict the long-range impact of average disasters on neighborhood change. As they mentioned, one of the limitations of their study is that the positive effects of a disaster of one size can be offset by the negative effects of disasters of other sizes. In the study by Pais and Elliot (2008), the case studies were three major hurricanes—Hurricane Bob in 1991, Andrew in 1992 and Opal in 1995. In their investigation, they did not control for the number of years following the hurricanes (i.e., the long-term impact). That is, they compared the impact of Hurricane Bob after nine years but that of Hurricane Opal after five years, regarding them as equal. However, because of the four-year discrepancy, the long-term effects of the two hurricanes cannot not be compared.

Another drawback of these two studies is that they did not provide appropriate control groups that allowed the researchers to generalize, with more confidence, what would take place in a neighborhood after a disaster. Wright et al. compared two groups: one that experienced at least one natural disaster and another that did not. However, the results of their analyses showed that the distinction between groups experiencing small-sized disasters and those experiencing no disasters was unclear. In their study, Pais and Elliott (2008) divided census tracts into three zones according to disaster severity. The control group consisted of tracts that were less affected by the three hurricanes. Nevertheless, one cannot determine whether the control groups of the affected neighborhoods nor the treatment of all of the groups were truly comparable because the criteria for defining the control group were unclear. Furthermore, in the spatial dimension, the control group was generally located inland while the treatment groups were located in coastal areas. However, coastal areas, regardless of the damage they sustain from a hurricane, are likely to become whiter, richer, and older. Thus, the choice of an inappropriate control group could have biased the results of the analysis.

An additional shortcoming of these studies is that they did not consider the number of natural disasters that had affected neighborhoods during the study period nor the time that had lapsed between the disasters. They assumed that neighborhoods in their study areas had been hit by just one major natural disaster during the ten-year study period. Pais and Elliot (2008), selecting three major hurricanes that occurred in the early 1990s, examined the long-term impact of these hurricanes on neighborhood change. Even though other neighborhoods had been hit by other major hurricanes in the middle or late 1990s (e.g., many neighborhoods in Louisiana were significantly affected by not only Hurricane Andrew in 1992 but also Hurricane Georges in 1998), they did not control for the impact of the additional hurricanes on neighborhood change during the study period. In addition, Wright et al. (1979) did not consider the time lapse between the disasters. By simply checking whether a neighborhood had been hit by at least one other natural disaster during their study period, they might have discovered that the "ignored" disaster affected neighborhood change differently. Thus, the findings of these studies might have been biased in two ways: First, the studies did not separate the impact of a specific natural disaster that they wanted to examine from the impact of other natural disasters that hit the neighborhoods in the study areas during the study periods. Second, they overlooked the variations in the impact of the natural disasters on neighborhood change in the interval between disasters.

Finally, the most serious shortcoming of the two studies is that they neither theoretically nor methodologically considered the historical or social context in which neighborhoods change. In general, neighborhoods change over time, even without natural disasters. These changes are "fundamentally driven by external forces reverberating through the metropolitan housing market" (Galster 2001, p. 2215). In this context, natural disasters are considered interventions in the path of neighborhood change. That is, the effect of natural disasters on neighborhood change should be understood as an intervening effect that influences the historical trend of neighborhood change. However, the two studies, dealing with two time spans—before and after natural disasters—overlooked the historical trend of neighborhood change and the impact of the interplay between the historical trend and the intervening natural disaster on neighborhood changes in the long-term.

Methodologically, the two studies estimated the long-range effects of natural disasters on neighborhood change, utilizing the "post-intervention, relative-change approach." Therefore, they may not have provided the appropriate baseline of comparison against which actual changes in the neighborhood indicators are measured to assess the putative impact of an intervention. As discussed above, if it does not provide accurate counterfactuals, this approach can lead to erroneous conclusion. In addition, the studies use traditional regression models with one time-lagged variable. One of the assumptions underlying traditional regression models is that observations are independent in terms of time and space. However, this assumption may be violated if a neighborhood changes over time, if the changes do not reflect a trend, if the natural disaster intervenes in the trend of the neighborhood change, and if the trend of the neighborhood change and the intervention effect of the natural disaster differ with regard to the characteristics of the neighborhood. If any of these conditions are indeed present, the use of traditional regression approaches will yield biased estimates of the relationships among the variables.

Furthermore, with this approach, it is difficult to separate the effects of the disasters from those of public policies applied in the form of relief and rehabilitation activities in the wake of the disaster (Rossi et al. 1981). The estimates for a long-term disaster effort include funds required for the disaster and the accompanying endogenous recovery efforts, aid given by political units and private organizations originating outside the disaster-stricken areas, and the financial repercussions in the housing market for both rental and owner-occupied units. In other words, neighborhood change in the long term results from not only the natural disasters themselves but also the reconstruction and recovery processes that follow the disasters.

CHAPTER 3

RESEARCH QUESTIONS AND HYPOTHESES

The purpose of this dissertation is to examine and to clarify how natural disasters intervene in the trend of neighborhood change. It seeks to identify the role of natural disasters in accelerating neighborhood transition by tracking changes in several indicators of neighborhood change over time and to determine variations in neighborhood change induced by natural disasters according to the intensity of disasters, the socioeconomic characteristics of neighborhoods, and the size of municipalities. These objectives are the basis of the research questions and hypotheses of this dissertation.

3.1. Research Questions

This dissertation explores the connection between natural disasters and neighborhood change by examining the following questions:

(1) Do natural disasters affect the trend of changes in the characteristics of neighborhoods? And if so, how do they affect them?

(2) Do the effects of natural disasters on neighborhood change differ according to the intensity of a disaster, and the characteristics of the neighborhoods and municipalities? In particular, are neighborhoods that sustain more severe damage from a disaster more likely to change (i.e., will they grow and improve or decline)? Are lower-income neighborhoods more likely to suffer from adverse change after the disasters? And are neighborhoods located in larger municipalities more likely to experience growth and improvement?

(3) Do natural disasters result in increasing the socioeconomic and racial disparity of the population?

To address these questions, this dissertation will test the following research hypotheses.

3.2. Hypotheses and Research Rationale

Based on the purpose and questions, this research proposes the following main hypothesis pertaining to the effects of natural disasters on neighborhood change:

H: Natural disasters affect the trend of neighborhood change, and neighborhood changes induced by the disasters result in increasing disparity of the residential population on a metropolitan neighborhood scale.

This main hypothesis will be largely disaggregated into three sub-dimensions: the intervention effect of a natural disaster on neighborhood change, the differential impact of the magnitude of a natural disaster on neighborhood change, the pre-disaster state of affected neighborhoods and the role of municipalities in the recovery process; and the increase in disparity of the population as an effect of a natural disaster.

H 1: Natural disasters significantly impact the trend of neighborhood change.

H 1-1: The number of natural disasters that hit neighborhoods and the time lapse between the disasters affect the trend of neighborhood change. A larger number of natural disasters are more likely to change the characteristics of a neighborhood, and a shorter time lapse between disasters is more likely to be linked to significant neighborhood change.

H 2: Natural disasters affect the trend of neighborhood change differently in the following ways:

H 2-1: Large natural disasters have a significant effect on neighborhood change. They are positively correlated with neighborhood change.

H 2-2: The socioeconomic condition of a neighborhood, especially income status, prior to a natural disaster significantly affects the state of the neighborhood in the aftermath. Low-income neighborhoods are more likely to be vulnerable to neighborhood change after a natural disaster compared to high-income neighborhoods.

H 2-3: Rehabilitation efforts by local governments, measured by the location of the local jurisdictions, dramatically affect neighborhood change. Neighborhoods in larger local jurisdictions are more likely to experience positive change (e.g. increase in income or property values) than those in smaller local jurisdictions.

H 3: Natural disasters result in increasing the socioeconomic and racial disparity of the residential population.

H 3-1: Natural disasters produce an increase in difference among neighborhoods.

Neighborhoods are believed to undergo a series of transformations that are cyclical or circular in nature (e.g., Grigsby et at. 1987; Rosenthal 2008). The natural disaster acts as an intervention in the normal time series of neighborhood change (Rossi et al. 1981). This intervention upsets the neighborhood and then accelerates neighborhood change. More specifically, a natural disaster above a specific size causes a population with specific socioeconomic characteristics to more likely relocate from the affected neighborhood to another neighborhood and then induces neighborhood change that diverges from its original path (i.e., it follows a different course from its intended course in the past) (Belcher and Bates 1983; Elliott and Pais 2006; Landry et al. 2007; Pais and Elliott 2008; Paxson and Rouse 2008; Smith and McCarty 1996). Figure 3-1 illustrates this change in the path of a neighborhood indicator induced by a natural disaster. An "observed" line (the solid line) represents the path of the neighborhood indicator before and after the disaster. An "expected" line (the dotted line) illustrates the extrapolated path of the indicator by the historical trend without the disaster. The magnitude of the difference between the observed and expected lines varies according to the intensity of the natural disaster, rehabilitation efforts, the neighborhoods, and time.

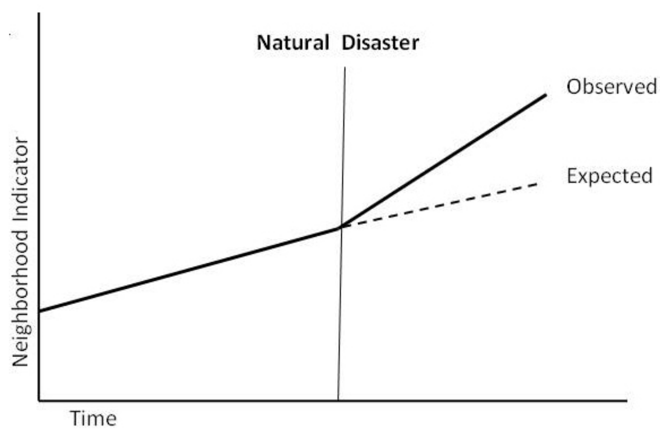


Figure 3-1. Impact of Natural Disasters on Neighborhood Change

Bates et al. (1963) explained that changes in the social system after a natural disaster result from two factors outside the system: the disaster itself and the rehabilitation process. Similarly, these factors from outside the neighborhoods are introduced to the neighborhoods, producing changes in their characteristics. If a disaster produces change, the change is believed to originate in new inputs introduced to a neighborhood that was in a particular state prior to their introduction. When a natural disaster occurs, neighborhoods are disrupted by the direct physical impact of the natural disaster. The degree of disruption depends on the magnitude of the disaster and the prior condition of the neighborhoods it strikes. Then, upon rehabilitation, the neighborhoods begin to take on a new form or state that will differ from the original pre-disaster state.

Figure 3-2 shows three types of change sequences in a neighborhood. The first, depicted by a thick solid line at the top that connects the various boxes representing the neighborhoods, represents change that was already underway in the neighborhood and that would have occurred without the disaster. In this figure, a neighborhood, regardless of the disaster, changes from time T_0 to time T_2 both socially and economically in the region in which the neighborhoods are located. "Neighborhood T_2" represents the state of the neighborhood at time T_2, manifested through systematic mechanisms, even without the disaster. The second, represented by the dotted line, depicts change that is the direct result of the disaster input, for example, damage or destruction to homes and schools. A "Disrupted Neighborhood" in the "Impact Phase" characterizes the state of the neighborhood directly affected by the disaster. The third, represented by a thin solid line at the bottom of the diagram depicts a change in the neighborhoods resulting from rehabilitation input, which is relief from government agencies. A "Disrupted Neighborhood" in the "Rehabilitation Phase" also shows disrupted neighborhoods resulting from rehabilitation input. Therefore, at time T_2, the neighborhood has different states according to the magnitude of the disaster and the rehabilitation inputs. "Neighborhood $T_{2\text{-}2}$" is the new state of the neighborhood affected by all of these three factors—the pre-disaster trend of the neighborhood change and the disaster and the rehabilitation input—at time T_2. If a neighborhood affected by one natural disaster is hit

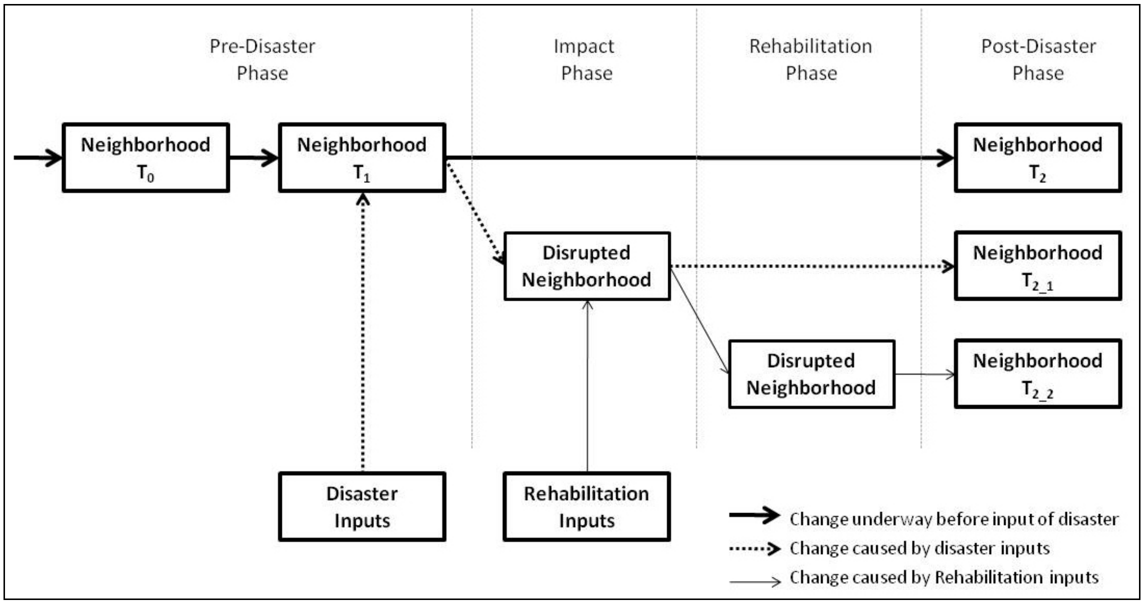


Figure 3-2. Process of Neighborhood Change in Response to Natural Disasters

by another major natural disaster, the neighborhood changes further, repeating the change process induced by the first natural disaster. The new state of the neighborhood will largely differ from the state of a neighborhood that has not experienced more than one natural disaster in the long-term.

These neighborhood changes accelerated by natural disasters increase disparity of residential populations. Such disparity may increase significantly following a major disaster for two reasons, both discussed in the literature review. First, the pattern of relocation after a natural disaster differs according to the socioeconomic or racial characteristics of a household (Dash et al. 1997; Frey and Singer 2006; Girard and Peacock 1997; Smith 1996; Smith and McCarty 1996). For example, after Hurricane Andrew, white and richer households left Miami-Dade County in greater numbers than blacks and the poor. By contrast, after Hurricane Katrina, low-income households left the New Orleans metropolitan area in greater numbers than other households. While researchers have not reached a consensus about which socioeconomic or racial groups are more likely to move frequently from one place to another after a natural disaster, they agree that the natural disaster clearly contributes to substantial population redistribution in affected neighborhoods. Accelerated population redistribution triggered by natural disasters increases disparity of neighborhoods through the processes of spatial assimilation and place stratification, which are the underlying mechanisms for controlling residential mobility in the United States (South, Crowler, and Chavez 2005).

Second, natural disasters affect neighborhood change differently according to the strength and the size of the municipality within a regional stratification system, which has important implications for the recovery processes. A large, strong local government, as a “recovery machine” (Pais and Elliott, 2008), can use its newfound resources and power to expand aggressively following a major disaster, increasing the local population and the number of housing units and newcomers during the time of recovery. By contrast, a small, weak local government within a stratified urban ecological network can either contribute to or be the result of continuing class and racial segregation. Dash et al. (1997) found that in a very small, predominantly black incorporated municipality, the proportion of the black population increased while that of the white population declined after Hurricane Andrew. However, in one large, predominantly white municipality, the proportions of white to black residents remained relatively equal, indicating that neighborhoods change in different ways according to the ability of a local government to deal with natural disasters. Therefore, if a local government has a weak ability to recover, it can exacerbate disparity among neighborhoods.

Figure 3-3 presents various effects of natural disasters on neighborhood change according to the socioeconomic characteristics of a neighborhood and more specifically on disparity among neighborhoods in the aftermath of a natural disaster. In particular, this dissertation focuses on variant changes in the economic status of neighborhoods after disasters (i.e., a high- or low-income neighborhood). In both neighborhoods, disaster and rehabilitation inputs affect the historical trends of their neighborhood change. However, the impact on these neighborhoods differs. Even without adequate rehabilitation input or other relief efforts by the government, high-income neighborhoods are likely to return to their prior state because the damage sustained from the disaster is typically fully covered by insurance, or they are able to recover

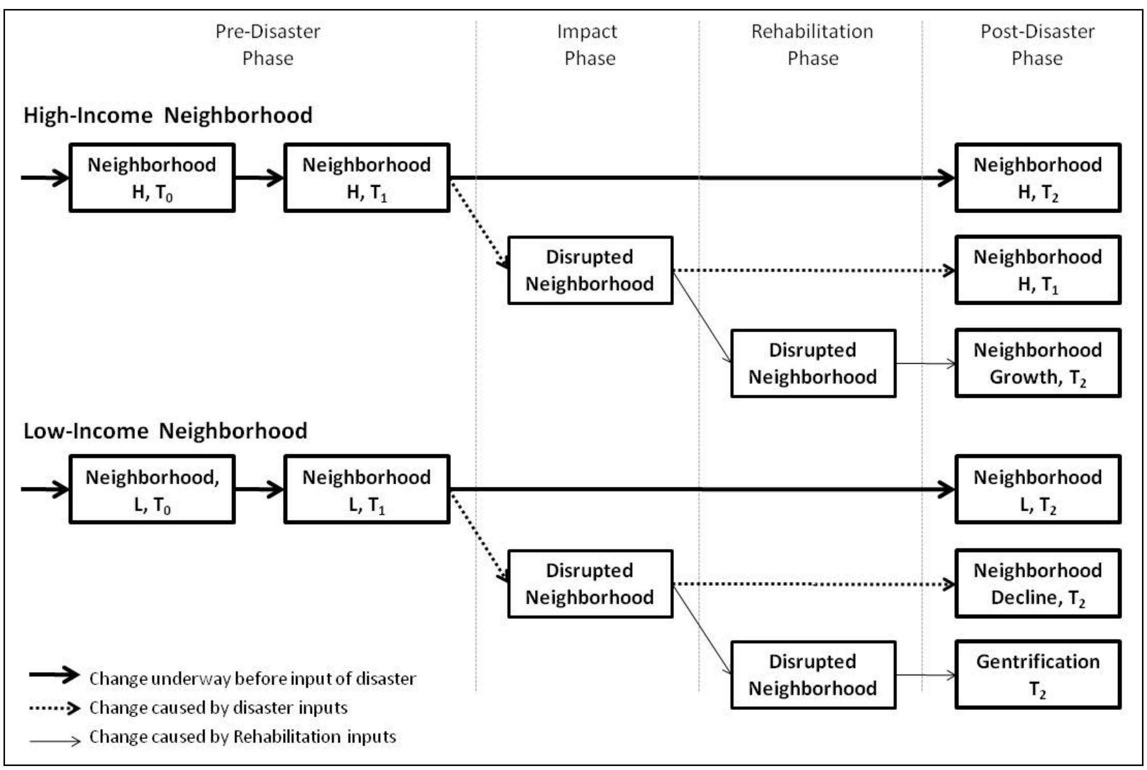


Figure 3-3. The Differential Impact of Natural Disasters on Neighborhood Change by Income

financially on their own (Browne and Hoyt 2000; Dixon et al. 2006; Kriesel andLandry 2004). By contrast, low-income individuals and neighborhoods cannot afford to repair or rebuild homes (Fothergill 2004), leading to their rapid deterioration (Dash et al. 1997).

In the rehabilitation phase, a high income neighborhood typically receives financial windfalls from the government, which, along with insurance claims, result in the growth of the neighborhood (Kamel and Loukaitou-Sideris 2004). However, any economic assistance flowing into low-income neighborhoods sustaining severe damage could have two very different outcomes: neighborhood revitalization (further gentrification) or neighborhood decline. With regard to the former, if the market foresees benefits from rebuilding low-income neighborhoods, strong local governments might promote redevelopment there; therefore, with such economic assistance, they are more likely to be revitalized and further gentrified (Lloyd 2005). With regard to the latter, neighborhood decline, low-income neighborhoods located in small municipalities with low exchange use in the market might be excluded from rehabilitation efforts fostered by economic assistance. Eventually, they suffer from serious physical deterioration that leads to their decline. Such divergent outcomes lead to neighborhood consisting of high- and low-income residents that increase more severely disparity of after a natural disaster than before: While high-income neighborhoods grow and improve in status, low-income neighborhoods decline.

CHAPTER 4

RESEARCH DESIGN

4.1. Case Study Areas, Analysis Units, and Data Sources

This dissertation selects metropolitan counties for the examination of the impact of natural disasters on neighborhood change and analyzes the differential impact across neighborhoods from 1970 through 2000. It seeks to analyze neighborhood changes in the areas affected by hurricanes that caused more than $1 billion in property damage in the 1980s for several reasons. First, their scale assures us that the disaster exerted a definitive impact on the observed region. That is, they were not simply incidental to other events occurring at or around the same time but actually caused the destruction of or damage to substantial portions of the built environment. Second, because of the times in which these hurricanes occurred in the 1980s, they may provide more reliable evidence of neighborhood change, especially in the trajectory of change, the reason being that by using census data, which provide four time points (1970, 1980, 1990, and 2000), two before and two after the disasters, we can more thoroughly estimate neighborhood change. Based on these two characteristics, we can focus on the impact of the hurricanes without any concern about the impact of any other disaster and efficiently examine the differential effects of the disaster as they relate to the variety of regional characteristics.

The Spatial Hazard Events and Losses Databases for the United States (SHELDUS), administered by the University of South Carolina, provide a county-level hazard data set for the United States from 1960 through 2008 (Hazards and Vulnerability Research

Institute 2009). The databases include dollar values of property damages from major natural disasters. Table 4-1 provides information from the database that shows major natural disasters including major hurricanes that caused more than $ 1 billion in property damage, between 1970 and 2000 in the United States. During the period, the United States was affected by twelve "billion dollar" hurricanes: Hurricane Agnes (1972), Allen (1980), Alicia (1983), Elena (1985), Gloria (1985), Hugo (1989), Bob (1991), Andrew (1992), Opal (1995), Fran (1996), Georges (1998), and Floyd (1999). Of these hurricanes, five hit the United States in the 1980s, which are highlighted in Table 4-1: Allen, Alicia, Elena, Gloria, and Hugo. This dissertation will focus on these five hurricanes to investigate their impact on neighborhood change.

Table 4-1. Major Natural Disasters between 1970 and 2000, U.S.A.

Year	Major Hurricanes	Year	Other Major Natural Disasters
1972	Agnes	1971	San Fernando Earthquake
1980	Allen	1980	Washington Eruption
1983	Alicia	1989	Loma Prieta Earthquake
1985	Elena	1991	California Wildfire
1985	Gloria	1993	Midwest Flood
1989	Hugo	1994	Northridge Earthquake
1991	Bob	1995	Severe Storm
1992	Andrew		
1995	Opal		
1996	Fran		
1998	Georges		
1999	Floyd		

Note: Major hurricanes and natural disasters mean hurricanes and natural disasters with property damages over one million dollars (2006 dollars based on the U.S. DOC Implicit Price Deflator for Construction).
Source: Hazards and Vulnerability Research Institute (2009).

According to Table 4-2, which shows their characteristics, the hurricane that caused the most severe damage was Hurricane Hugo in 1989. Hugo was a category 4 hurricane, indicating wind speeds that can cause extreme damage to affected areas. The total dollar value of damages by Hugo exceeded $13 billion (in 2006 dollars). By contrast, Hurricane Gloria in 1985 caused comparatively small dollar damage, about $1.7 billion. These five hurricanes mainly affected areas in seven states: Alabama, Florida, Louisiana, Mississippi, North Carolina, South Carolina and Texas.

Table 4-2. Major Hurricanes in the 1980s, U.S.A.

Hurricanes	Year	Category	Affected Areas	Damage (in millions of dollars)
Allen	1980	5	TX	3,850
Alicia	1983	3	TX	4,825
Elena	1985	3	AL & MS	2,848
Gloria	1985	4	NC & LI	1,680
Hugo	1989	4	NC & SC	13,480

Note: Damages were estimated according to their value in 2006 dollars based on the U.S. DOC Implicit Price Deflator for Construction.
Source: Blake, Rappaport, Landsea and National Hurricane Center (2007).

The SHELDUS database can also help to identify the number of neighborhoods affected by major hurricanes and their location. Using the database, this dissertation mainly analyzes a study area comprising the counties hit by these five major hurricanes in the 1980s. Of these counties, in particular, those in the metropolitan areas are the focus of this study, for the results may be more meaningful because most of U.S. population resides in these areas. According to SHELDUS, the total number of metropolitan counties affected by hurricanes only in the 1980s was 95; and the total number of not affected by any major disasters between 1970 and 2000 was 454. Figure 4-1 illustrates the location of these U.S. metropolitan counties and the tracks of major hurricanes in the 1980s.

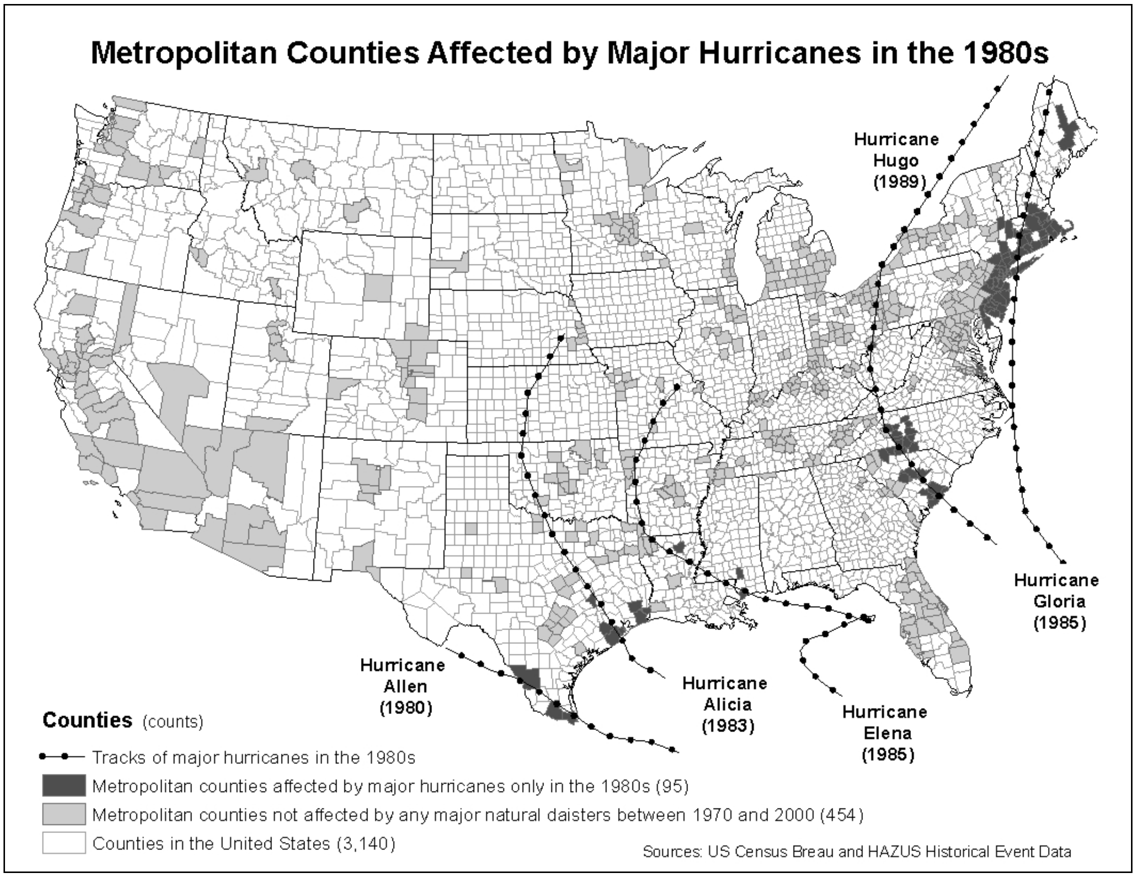


Figure 4-1. U.S. Metropolitan Counties Affected by Major Hurricanes Only in the 1980s

Investigating the impact of the major hurricanes on neighborhood change, this dissertation uses the census tract, a proxy for a neighborhood, as the unit of analysis. On average, census tracts include 4,000 people, and the Census Bureau demarcates tract boundaries so that residents of a given tract share similar socioeconomic characteristics. To examine neighborhood change over time, many studies have also used the census tract as the unit of analysis (i.e., Ellen and O'Regan 2008; Galster and Mincy 1993; Galster et al. 2003; Pais and Elliott 2008). Thus, this dissertation focuses on census tracts in US metropolitan counties affected by hurricanes only in the 1980s, controlling for the census tracts in other US metropolitan counties not hit by any major natural disasters.

Using SHELDUS, this dissertation defines the treatment group as the census tracts in the U.S. metropolitan counties that have been hit by one of five major hurricanes only in the 1980s. The control group consists of the census tracts in U.S. metropolitan counties that have never been affected by any major natural disasters, including hurricanes, from 1970 through 2000. The total number of census tracts in U.S. metropolitan counties (95) affected by hurricanes in the only 1980s (i.e., treatment group) is 9,419. The total number of census tracts in metropolitan counties (454), which have never affected by any natural disasters during the study period (1970 through 2000) (i.e., control group), is 25,918.

Furthermore, this study differentiates the census tracts in the treatment group according to the level of severity of the physical damages caused by the major hurricanes in the 1980s, using HAZUS-MH software. HAZUS-MH, developed by the Federal Emergency Management Agency (FEMA), is generally used to estimate the physical damages and the social and economic losses from the natural disasters for the United States. Of the many functions on the software, the historical event modeling function enables one not only to delineate the exact census tracts affected by the historical major natural disasters but also to estimate the physical damage for each census tract. This dissertation uses HAZUS-MH to estimate the differential impacts of major hurricanes on neighborhood change according to the degree of the physical damages.

The primary data source was the Neighborhood Change Database (NCDB), produced by GeoLytics, which contains longitudinal Census Long and Short Form Data of 1970, 1980, 1990, and 2000. The database is the only source of tract-level census data in which tract boundaries have been delineated consistently over time. The compelling strength of this dataset is that it links census tracts as they were defined in the 2000 census, thus permitting us to examine how neighborhoods changed over a three-decade period with constant geographical units of analysis. The data for the cases of natural disasters came from SHELDUS. The database provides total property damage for major historical natural disasters and total property damage per county.

4.2. Research Methodology: Longitudinal Model

This dissertation uses the longitudinal model as a main methodology for examining the impact of natural disasters on neighborhood change. Consulting longitudinal data pertaining to the values of neighborhood indicators between 1970 and 2000, this dissertation hypothesizes that natural disasters intervene in the trend of neighborhood change over time and that their impact varies according to the profile of the neighborhood. These two hypotheses provide a strong rationale for using longitudinal modeling in this dissertation. The following sections introduce the longitudinal models that deal with change over time (the level-1 observations) and variance in individual units (the level-2 observations) and present the discontinuous changes that take place in neighborhoods affected by natural disasters and the variability in the change patterns of neighborhoods with their characteristics.

4.2.1. Rationale for the Use of the Longitudinal Model

This dissertation refers to the longitudinal model because it more concisely explains the impact of natural disasters on neighborhood change both conceptually and methodologically. In the conceptual aspect, the longitudinal model efficiently outlines several important hypotheses of this dissertation: (1) neighborhoods continue to change over time without any intervention such as natural hazards; (2) the patterns of neighborhood change vary according to the characteristics of neighborhoods; and (3) natural disasters act as an intervention in the normal time series of neighborhood change and then accelerates change. According to Singer and Willett (2003), the longitudinal model treats two types of questions that every study pertaining to change (referred to here as "neighborhood change" in this work) attempts to answer. The first type, consisting of descriptive questions, seeks to characterize the pattern of change of each neighborhood over time. The questions include the following: Do neighborhoods change over time? Is neighborhood change linear or nonlinear? Is the change consistent over time, or does it fluctuate? The second type of questions, which are relational, examine the association between the predictors and the patterns of change and include the following: Do different types of neighborhoods experience different patterns of change? Which predictors are associated with which patterns? In addition, the model tracts changes in the trends of neighborhood change after intervention, offering discontinuous models for change. The model can successfully address and answer these questions because it estimates the trajectories of change using time-series data and separates the two different types of questions (changes over time within neighborhoods and variations among neighborhoods) using multilevel models.

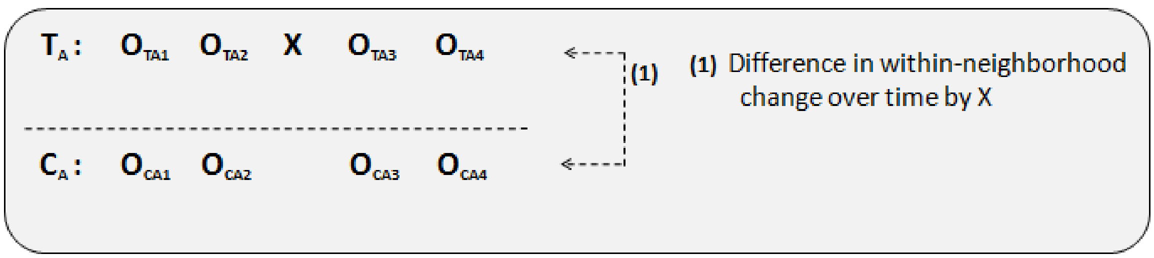
In the methodological aspect, the longitudinal model provides more sophisticated estimation of the impact of natural disasters on neighborhoods change in two ways. First, the model efficiently estimates the impact of natural disasters on neighborhood change by providing a superior counterfactual that can be estimated by considering both pre- and post-intervention information in affected neighborhoods. Most research pertaining to both the impact of intervention such as public policy and natural disaster studies and neighborhood trajectories have employed the "post-intervention, relative-change approach" (Galster et al. 2006, p. 457). Such studies have compared neighborhood changes observed during the period in which an intervention had an impact to determine whether they coincided with changes in the control neighborhoods (e.g., Pais and Elliott 2008; Smith 2003; Wright et al. 1981; Zielenbach 2003). The counterfactual is assumed to consist of changes observed in the control neighborhoods that indicate a difference in levels between pre- and post-intervention, so only the relative advantages of the intervention over the control neighborhoods are taken as evidence of an impact (Galster et al. 2006). However, "pre- and post-intervention comparisons of levels alone may obscure significantly different slopes before and after an intervention" (Galster et al. 2004, p.512). In particular, the counterfactual may be seriously misleading if the affected neighborhoods had been undergoing substantial change before the intervention compared to control neighborhoods and if no sufficient observations were to help us establish indicator slopes both before and after an intervention.

Galster and his colleagues (2004) introduced the Adjusted Interrupted Time Series (AITS) Model to makes up for these weaknesses by comparing the trends as well as levels in the changes before those occurring after the intervention within affected neighborhoods. That is, affected neighborhoods serve as their own counterfactual by extrapolating the pre-intervention trends in the outcomes indicators of affected neighborhoods in the post-intervention period. This approach helps to reduce errors from any variation between the affected and control neighborhoods. The longitudinal model plays a same role with the AITS model in estimating the trends before and after the intervention, using time series data. For better estimation, these models use two counterfactuals: pre- and post-intervention, and test and control neighborhoods. They help establish a convincing counterfactual with which actual changes in affected neighborhoods can be compared, allowing us to plausibly deduce causation (Shadish et al. 2002).

The second way in which the longitudinal model provides more sophisticated estimation of the impact of natural disasters on neighborhood change is that it allows for inter-neighborhood heterogeneity in neighborhood change, using multilevel data. It is characteristic that separates this model from the AITS model, suggesting that the longitudinal model could better explain the differential impacts of natural disasters on neighborhood change according to neighborhood characteristics.

Figure 4-2 presents a comparison of the longitudinal model with the AITS model. T and C represent the treatment group and the control groups, respectively. O_{TA1} illustrates the observation of the treatment group A at time 1, and X symbolizes an intervention such as a natural disaster that changes the trend of the observation trajectory. Using time series data, the AITS model estimates the intervention impact of X on the historical trend of neighborhood change. It compares the variations in the trends of neighborhood change after intervention X in the treatment group with those of neighborhood change in the control group. This approach treats differences in within-neighborhood change caused by intervention X over time. By contrast, the longitudinal model estimates the differential impact of intervention X on the historical trend of neighborhood change according to the characteristics of neighborhoods. To compare the trends in the treatment group and in the control group, it estimates not only the impact of the intervention on neighborhood change, but also the differential impact of the intervention on Groups A and B. Thus, the longitudinal model deals with not only differences in within-neighborhood change over time but also inter-neighborhood differences in change and the interaction between both.

< The Adjusted Interrupted Time Series Model>



< The Longitudinal Data Model>

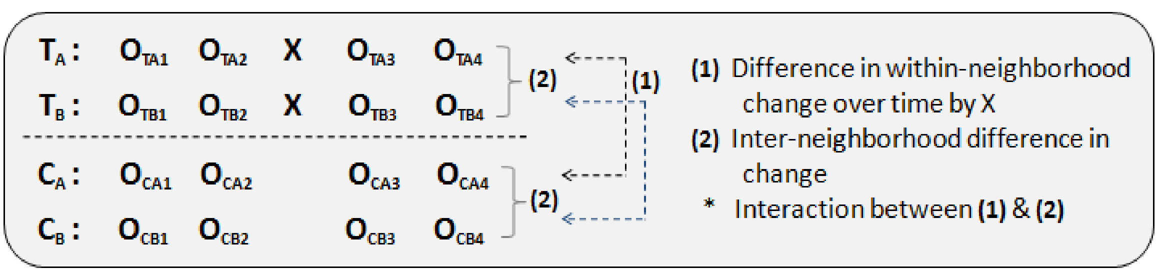


Figure 4-2. Comparison of the Longitudinal Model with the AITS Model

One of the assumptions underlying traditional regression models, including the AITS model, is that observations are independent, indicating the independence and the homoscedasticity of residuals. The results of the regression models demonstrate the shape of the average neighborhood change trajectory—the average initial status and the average rate of change in the sample as a whole. However, this assumption may be violated if a neighborhood changes over time, if the changes reflect a trend, if the natural disaster intervenes in the trend of the neighborhood change, and if the trend of the neighborhood change and the intervention effect of the natural disaster differ with regard to the characteristics of the neighborhood. If any of these variables are indeed the case, the use of traditional regression approaches will yield biased estimates of the relationships among the variables. As a result, the traditional regression model will imperfectly measure true initial status and true rate of change of each neighborhood over time.

The longitudinal model is likely to hold in longitudinal data in which residuals tend to be autocorrelated and heteroscedastic over time within neighborhoods (Singer and Willett 2003). The model measures the impact of natural disasters on neighborhood change on multiple levels such as within-neighborhood change and between-neighborhood differences in change. The distinction between the within-neighborhood and the between-neighborhood questions provides the core rationale for specifying a statistical model for change, which clarifies that "something" observed within-neighborhood is related to "something" observed between-neighborhoods. Thus, the longitudinal model, using multiple levels for change, quantifies the amount of inter-neighborhood difference in change and further explores the mixed, or interactive effects of neighborhood characteristics in terms of the relationship between natural disasters and neighborhood change. This interaction allows researchers to determine whether the causal effects of the lower-level predictors (i.e., natural disasters) are moderated by the higher-level predictors (i.e., neighborhood characteristics), the most salient factor that distinguishes the longitudinal model from the AITS model and the strongest rationale for using longitudinal modeling in this dissertation.

In summary, the longitudinal model provides a more sophisticated estimate of the differential effects of natural disasters on neighborhood change in two ways. First, like the AITS approach, the model, using time series data, provides a superior counterfactual that consider both the levels and the slopes in the changes before and after intervention. Second, unlike AITS, the model, using multiple levels, allows for inter-neighborhood heterogeneity in neighborhood change. It accounts for the interaction among different levels of change to determine whether the causal effects of the lower-level predictors (i.e., natural disasters) are moderated by the higher-level predictors (i.e., neighborhood characteristics).

4.2.2. Basic Concept of the Longitudinal Model

A number of researchers have empirically investigated the phenomenon of change, also referred to as individual growth models, random coefficient models, multilevel models, mixed models, and hierarchical linear models. The longitudinal model is recognized as a "multilevel model for change" (Singer and Willett 2003, p. 45). In general, the model analyzes change divided into two stages. In the first stage, known as *level-1*, one examines within-neighborhood change over time to characterize the individual growth trajectory of each neighborhood so that its outcome values rise and fall over time. In the second stage, known as *level-2*, one investigates inter-neighborhood differences in change by assessing whether different neighborhoods manifest patterns of within-neighborhood change and asking what predicts these differences. Thus, a level-2 analysis detects heterogeneity in change across neighborhoods and determines the relationship between the predictors and the shape of the growth trajectory of each neighborhood. Ultimately, these two models are considered a "linked pair," referred to jointly as a "multilevel model for change" (Singer and Willett 2003).

The level-1 analysis of the longitudinal model, known as the "individual growth model," is similar to that of OLS regression: An outcome is predicted as a function of a linear combination of one or more level-1 variables plus an intercept. The basic model at level-1 is specified as

$$Y_{ij} = \beta_{0i} + \beta_{1i} TIME_{ij} + \varepsilon_{ij} \tag{1}$$

Y_{ij}, the value of neighborhood i at time j, is a linear function of time on that occasion ($TIME_{ij}$); β_{0i} represents the true initial status of neighborhood i, the value of the outcome when $TIME_{ij} = 0$; β_{1i} represents the true rate of change in neighborhood i during the period under study; and ε_{ij} represents that portion of the outcome of neighborhood i that is unpredicted on occasion j. This model assumes that a straight line adequately represents the true change of each neighborhood over time and that any deviation from the linearity observed in the sample data results from a random measurement error (ε_{ij}). However, because each neighborhood has its own individual growth parameters (i.e., intercepts and slopes), different neighborhoods can exhibit distinct change trajectories.

Thus, the level-1 intercept and slope can be viewed as functions of variables from level-2 predictors, which represent the specific characteristics of an individual neighborhood. In the level-2 model, a relationship between an individual growth parameter and the predictor is separately specified. Each level-2 model should ascribe differences in either β_{0i} or β_{1i} to some specific characteristics of an individual neighborhood, just as in a regular regression model. These two level-2 models are illustrated as

$$\beta_{0i} = \gamma_{00} + \gamma_{01} X_i + \zeta_{0i} \tag{2}$$
$$\beta_{1i} = \gamma_{10} + \gamma_{11} X_i + \zeta_{1i} \tag{3}$$

γ_{00} and γ_{10}, the level-2 intercepts, represent the average initial status of the population and the rate of change for $X = 0$. γ_{01} and γ_{11}, respectively; the level-2 slopes represent the effect of X on the change trajectories, providing increments (or decrements) to the initial status and rates of change and ζ_{0i} and ζ_{1i}, the level-2 residuals, represent portions of the initial status or the rate of change that is unexplained at level-2. They indicate deviations of the individual change trajectories around their respective group average trends. Taken together, the two components treat the intercept (β_{0i}) and the slope (β_{1i}) of an individual growth trajectory as level-2 outcomes that may be associated with the predictor, X. Substitution of formulas (2) and (3) into (1) yields a combined model as follows:

$$\begin{aligned} Y_{ij} &= \beta_{0i} + \beta_{1i} TIME_{ij} + \varepsilon_{ij} \\ &= (\gamma_{00} + \gamma_{01} X_i + \varsigma_{0i}) + (\gamma_{10} + \gamma_{11} X_i + \varsigma_{1i}) \times TIME_{ij} + \varepsilon_{ij} \\ &= \gamma_{00} + \gamma_{01} X_i + + \gamma_{10} TIME_{ij} + \gamma_{11} X_i TIME_{ij} + (\varepsilon_{ij} + \varsigma_{0i} + \varsigma_{1i} TIME_{ij}) \end{aligned} \tag{4}$$

Through this process, we accurately model the effects of both variables level-1 (γ_{10} $TIME_{ij}$) and level-2 (γ_{01} X_i) on the outcomes. In addition, as both the slope and the intercept are predicted, we can model cross-level interaction (γ_{11} X_i $TIME_{ij}$) in an attempt to understand what explains the differences in the relationship between the level-1 variable and the outcome.

This longitudinal model carries some basic assumptions: (1) Errors in the level-1 model are normal random variables with mean zero and common variance σ^2; (2) errors in the level-2 model are bivariate normal random variables with mean zero; and (3) level-1 and level-2 errors are uncorrelated, which indicates that the errors in the slopes and the intercepts are uncorrelated with a level-1 error.

4.2.3. Longitudinal Models of Discontinuous Change

Most multilevel models for change assume that individual growth is smooth. Individual, however, change can also be discontinuous. If we have reason to believe that individual change trajectories shift in elevation and/or slope, the level-1 model should reflect this hypothesis, which allows us to test ideas about how the shape of a trajectory changes over time, in this case, how the trajectory of a neighborhood indicator changes as a result of not only time but also the disaster experience. Figure 4-3 represents a change in the shape of neighborhood change trajectory induced by a natural disaster. It shows a change in decennial trends for four time points (1970, 1980, 1990, and 2000). The empirically estimated change trajectory for neighborhoods not affected by the disaster are represented by A-A'-A''. After the disaster, the neighborhood indicator in the impact neighborhoods shifts up to a higher level (A-A'-B).

To postulate a discontinuous individual change trajectory, we need to know not only why but also when the shift occurred. This notion that individual trajectories suddenly shift in elevation or slope for identifiable reasons has many applications. Figure 4-3 illustrates three discontinuous models for change (Singer and Willett 2003):

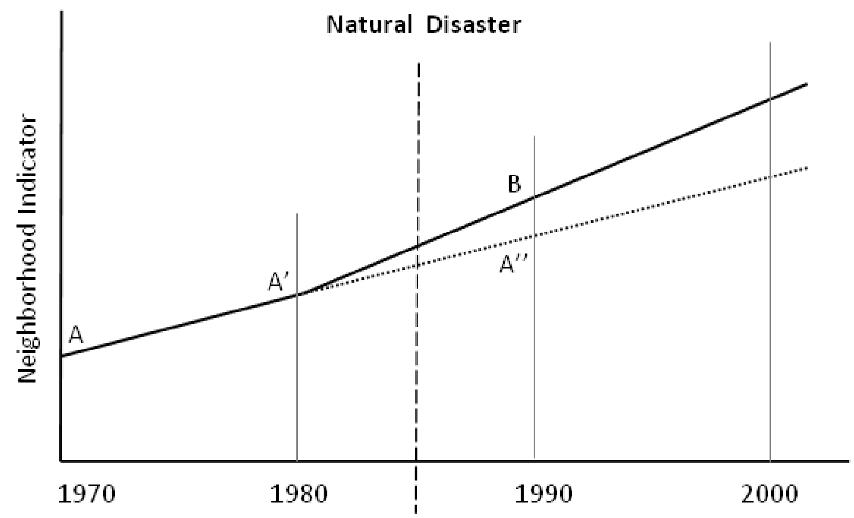
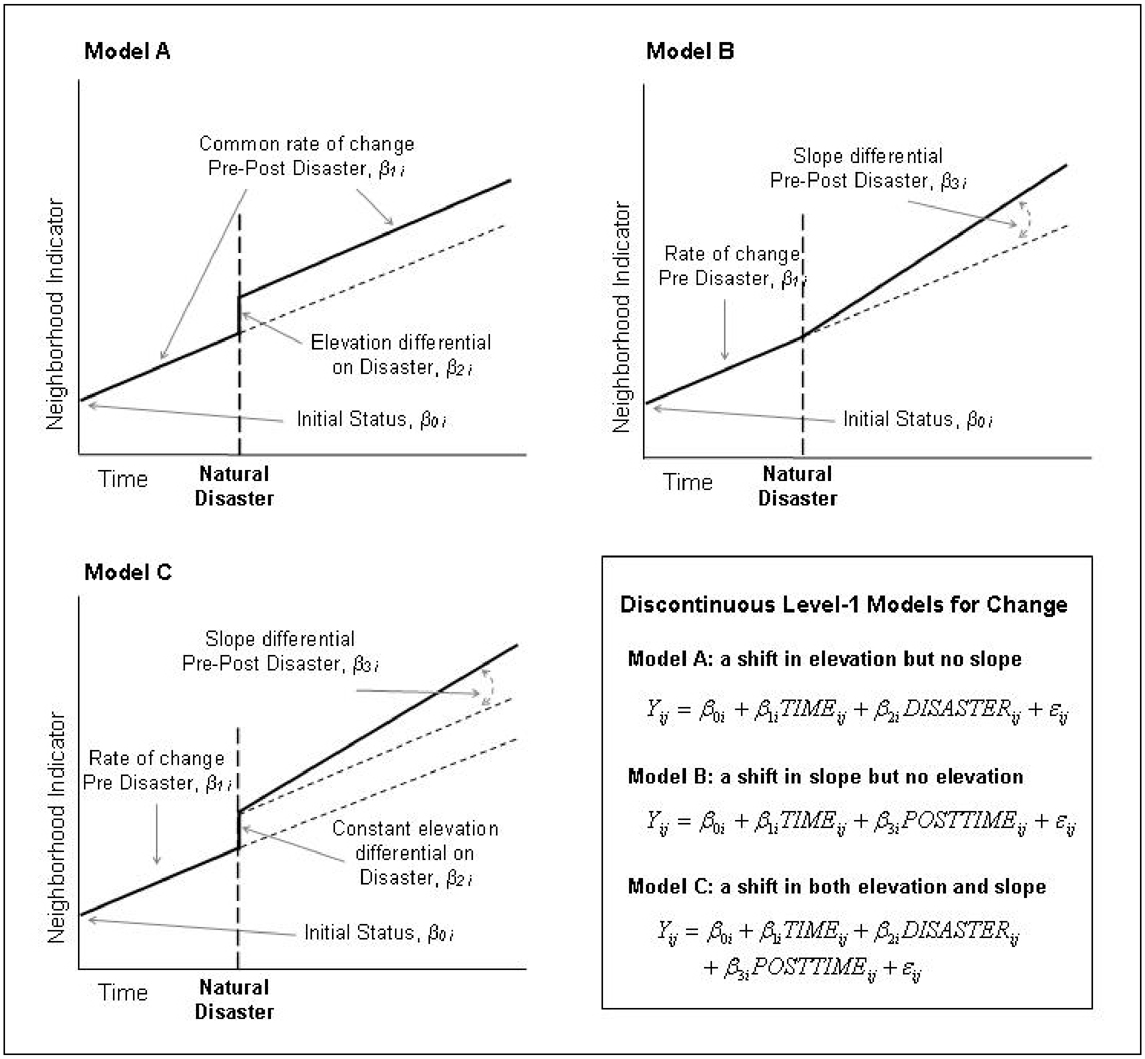


Figure 4-3. Discontinuous Trajectories of Neighborhood Change by a Natural Disaster

1. An immediate shift in elevation but no shift in slope (Model A in Figure 4-4). The value of the indicator of neighborhood *i* increases abruptly upon a disaster input, but its subsequent rate of change is unaffected, indicating that the elevation of its level-1 trajectory jumps, but its slope in the pre- and post-disaster epochs remain the same. A level-1 individual growth model of this type can be specified by adding the time-varying predictor $DISASTER_{ij}$ to the level-1 linear-change model in equation (1):

$$Y_{ij} = \beta_{0i} + \beta_{1i} TIME_{ij} + \beta_{2i} DISASTER_{ij} + \varepsilon_{ij} \qquad (5)$$

Because $DISASTERr_{ij}$ distinguishes the pre- and post-disaster epochs for neighborhood *i*, it permits the elevation of its trajectory to differ from disaster to disaster. Individual growth parameter β_{2i} presents the magnitude of this shift, which is identical regardless of when the disaster occurred because $DISASTER_{ij}$ takes on only two values, (0 and 1). Thus, two line segments exhibit identical slope β_{1i}, but different intercepts: β_{0i}, pre-disaster and ($\beta_{0i} + \beta_{2i}$), post-disaster.



Note: Modified from a figure in Singer and Willett (2003, p. 196).

Figure 4-4. Alternative Discontinuous Change Trajectories for the Influence of a Natural Disaster on Neighborhood Change

2. An immediate shift in slope but no shift in elevation (Model B in Figure 4-4). The value of the indicator of neighborhood *i* remains stable upon the occurrence of a disaster, but its subsequent rate of change increases, indicating that the elevation of

the level-1 trajectory is no higher after the occurrence of the disaster, but its slope in the pre- and post-disaster epochs differs. A level-1 individual growth model of this type can be created by adding a new time-varying predictor $POSTTIME_{ij}$, which clocks years beginning with the year the disaster occurred, the level-1 linear-change model in Equation 1:

$$Y_{ij} = \beta_{0i} + \beta_{1i}TIME_{ij} + \beta_{3i}POSTTIME_{ij} + \varepsilon_{ij} \tag{6}$$

Before neighborhood *i* experiences a disaster, the *POSTTIME* is 0, one year after the disaster, the *POSTTIME* is 1, and in subsequent years, the value continues to increase. Thus, before a disaster occurs, the slope of the trajectory of neighborhood *i* is β_{1i}. After the disaster, the neighborhood has the same intercept as the pre-disaster segment, but it has two slopes because of a one-unit increase in *TIME* resulting from a one-unit increase in the *POSTTIME*. As a result, the slope of the post-disaster trajectory is $(\beta_{1i} + \beta_{3i})$.

3. Immediate shifts in both the elevation and the slope (Model C in Figure 4-4). The value of the indicator of neighborhood *i* changes in two ways as a result of a disaster: It abruptly rises and the subsequent rate of change increases. These changes indicate that both the elevation and the slope of the level-1 trajectory differ pre- and post-disaster. A level-1 individual growth model of this type can be expressed by adding both $DISASTER_{ij}$ and $POSTTIME_{ij}$ to the basic level-1 individual growth model:

$$Y_{ij} = \beta_{0i} + \beta_{1i}TIME_{ij} + \beta_{2i}DISASTER_{ij} + \beta_{3i}POSTTIME_{ij} + \varepsilon_{ij} \tag{7}$$

Before the disaster, both *DISASTER* and *POSTTIME* are 0, and the linear-change trajectory is the same as that in Equation 1: $Y_{ij} = \beta_{0i} + \beta_{1i}TIME_{ij} + \varepsilon_{ij}$. After the occurrence of the disaster, *DISASTER* becomes 1 and *POSTTIME* begins its steady climb along with *TIME*, yielding a post-disaster trajectory with a different intercept and two slopes:

$$Y_{ij} = (\beta_{0i} + \beta_{2i}) + \beta_{1i} TIME_{ij} + \beta_{3i} POSTTIME_{ij} + \varepsilon_{ij} \qquad (8)$$

4.2.4. Model Specifications for the Impact of a Disaster on Neighborhood Change

Referring to the discontinuous models specified in Figure 4-4, this dissertation will specify the longitudinal models for application to the problems addressed in the dissertation and answer the following questions: How do some motivations for the longitudinal model lead to the alternative models represented in Figure 4-4? Which model can more effectively be applied to answer the research questions in this dissertation? To examine whether natural disasters and which patterns affect trends of neighborhood change, this dissertation employs Model C which presents immediate shifts in both the elevation and the slope. The model is more effective at showing changes in both the elevation and the slope of neighborhood change trajectory after natural disasters into one model.

As mentioned in the previous chapter, this dissertation attempts to answer three main questions: (1) Do natural disasters change the trends of neighborhood change? (2) Do different types of neighborhoods experience differential effects of the natural disasters? and (3) Which predictors are associated with which pattern? To address the third question, this dissertation considers three predictors associated with the differential impact of natural disasters on neighborhood change: two factors outside a neighborhood (the natural disaster itself and rehabilitation inputs) and one factor inside the neighborhood (the economic status).

First, do natural disasters have a significant impact on a neighborhood and what is the pattern of the impact? To answer these questions, this study uses the discontinuous level-1 model in Figure 4-4. The level-2 model will not be included here because the questions deal with the general pattern of the influence of a natural disaster on neighborhood change, not the differences among the effects on neighborhoods. Controlling for the major predictors affecting neighborhood change, we display the basic disaster-impact model as follows:

$$Y_{ij} = \beta_{0i} + \beta_{1i} TIME_{ij} + \beta_{2i} DISASTER_{ij} + \beta_{3i} POSTTIME_{ij} + \beta_{4i} NS_{ij} + \beta_{5i} NH_{ij} + \beta_{6i} M_{ij} + \varepsilon_{ij} \quad (9)$$

NS_{ij} and NH_{ij} represent the characteristics of the housing structure and the households of neighborhood *i* at time *j*, respectively. M_{ij} represents the characteristics of the metropolitan area in which neighborhood *i* is located at time *j*. These basic models can be expanded to more complex models by adding the variable of the second natural disaster that hit the neighborhoods. The expanded models would estimate the differential impact of natural disasters on neighborhood change according to the number of natural disasters that hit the neighborhoods and the time lapse between the natural disasters. The expanded models can be expressed as

$$\begin{aligned} Y_{ij} = {} & \beta_{0i} + \beta_{1i} TIME_{ij} + \beta_{2i} DISASTER\_1_{ij} + \beta_{7i} DISASTER\_2_{ij} + \beta_{3i} POSTTIME\_1_{ij} \\ & + \beta_{8i} POSTTIME\_2_{ij} + \beta_{4i} NS_{ij} + \beta_{5i} NH_{ij} + \beta_{6i} M_{ij} + \varepsilon_{ij} \end{aligned} \quad (10)$$

$DISASTER\_1_{ij}$ and $DISASTER\_2_{ij}$ represent the dummy variables that indicate the first and the second natural disasters that hit neighborhood *i* at time *j*, respectively.

$POSTTIME\_1_{ij}$ and $POSTTIME\_2_{ij}$ illustrate the times lapse between the first and the second disasters that hit neighborhood *i* at time *j*, respectively.

Second, does the influence of a natural disaster on neighborhood change vary across neighborhoods? This question regards whether a systematic variation worth exploring occurs in the outcome and how much total variation occurs both within and between neighborhoods. This information will facilitate the evaluation of a baseline amount of change. To answer this question, this dissertation employs the unconditional growth model, which includes only level-1 predictors and no substantive level-2 predictors. Based on Equation 8, the unconditional growth model will be

$$Y_{ij} = \beta_{0i} + \beta_{1i} TIME_{ij} + \beta_{2i} DISASTER_{ij} + \beta_{3i} POSTTIME_{ij} + \beta_{4i} NS_{ij} + \beta_{5i} NH_{ij} + \beta_{6i} M_{ij} + \varepsilon_{ij} \quad (9)$$

$$\begin{array}{lll} \beta_{0i} = \gamma_{00} + \zeta_{0i} & \beta_{3i} = \gamma_{40} + \zeta_{4i} & \beta_{6i} = \gamma_{50} + \zeta_{5i} \\ \beta_{1i} = \gamma_{10} + \zeta_{1i} & \beta_{4i} = \gamma_{40} + \zeta_{4i} & \\ \beta_{2i} = \gamma_{20} + \zeta_{2i} & \beta_{5i} = \gamma_{60} + \zeta_{6i} & \end{array} \quad (11)$$

We can express these two level models in composite form:

$$\begin{aligned} Y_{ij} = {} & \gamma_{00} + \gamma_{10} TIME_{ij} + \gamma_{20} DISASTER_{ij} + \gamma_{30} POSTTIME_{ij} + \gamma_{40} NS_{ij} + \gamma_{50} NH_{ij} + \gamma_{60} M_{ij} \\ & + (\varepsilon_{ij} + \varsigma_{0i} + \varsigma_{1i} + \varsigma_{2i} + \varsigma_{3i} + \varsigma_{4i} + \varsigma_{5i} + \varsigma_{6i}) \end{aligned} \quad (12)$$

This model can show the occurrence of variations in five predictors and the intercept at level-1 across neighborhoods. To answer this question, we focus, in particular, on the variation in *DISASTER*. If the variation of *DISASTER* is not significantly zero, the impact of a natural disaster on neighborhood change varies across neighborhoods.

Third, how do predictors explain the varying impact of natural disasters across a neighborhood? The major predictors of the differential impact of natural disasters on neighborhood change are (1) the natural disaster itself, (2) rehabilitation inputs, and (3) the economic status of the neighborhood. That is, these predictors allow for stochastic variation in the growth parameter, *DISASTER,* in the level-2 models, whose underlying assumptions are that the intercept and the slope in the level-1 model vary with the economic status of the neighborhood, indicating that the initial status and the growth rate of a neighborhood indicator vary with the economic status of the neighborhood.

Based on Equation 9, the model for the intensity of a natural disaster can be represented as follows:

$$
\begin{array}{ll}
\beta_{0i} = \gamma_{00} + \gamma_{01} INCOME_i + \zeta_{0i} & \beta_{3i} = \gamma_{30} + \gamma_{31} INTENSITY_i + \zeta_{3i} \\
\beta_{1i} = \gamma_{10} + \gamma_{11} INCOME_i + \zeta_{1i} & \beta_{6i} = \gamma_{50} + \zeta_{5i} \\
\beta_{2i} = \gamma_{20} + \gamma_{21} INTENSITY_i + \zeta_{2i} & \beta_{4i} = \gamma_{40} + \zeta_{4i} \\
 & \beta_{5i} = \gamma_{60} + \zeta_{6i}
\end{array} \tag{13}
$$

Substitution of the formula (12) into (8) yields a combined model as follows:

$$
\begin{aligned}
Y_{ij} = \gamma_{00} &+ \gamma_{01} INCOME_i + \gamma_{10} TIME_{ij} + \gamma_{11} INCOME_i TIME_{il} \\
&+ \gamma_{20} DISASTER_{ij} + \gamma_{21} INTENSITY_i DISASTER_{ij} \\
&+ \gamma_{30} POTTIME_{ij} + \gamma_{31} INTENSITY_i POSTTIME_{ij} + \gamma_{40} NS_{ij} + \gamma_{50} NH_{ij} + \gamma_{60} M_{ij} \\
&+ (\varepsilon_{ij} + \varsigma_{0i} + \varsigma_{1i} TIME_{ij} + \varsigma_{2i} DISASTER_{ij} + \varsigma_{3i} POSTTIME_{ij} + \varsigma_{4i} + \varsigma_{5i} + \varsigma_{6i})
\end{aligned} \tag{14}
$$

$INCOME_i$ represents the economic status of neighborhood *i* at a certain time; and $INTENSITY_i$ represents the magnitude of a natural disaster that neighborhood *i* experiences when the disaster occurs. Before the disaster, *INTENSITY* is zero and after the event, *INTENSITY* starts to take on a value related to the magnitude of the disaster. The value is consistent with time. This model can show that the intercept and the slope vary with neighborhood income before a disaster and that after the disaster, the intercept changes according to the disaster itself and its intensity as well as the neighborhood income. Thus, the model indicates the random effects of the intensity of the natural disaster and explains whether the effects of the predictors are uniform or heterogeneous, containing cross-level interactions, $INCOME_i TIME_{ij}$, $INTENSITY_i DISASTER_{ij}$ and $INTENSITY_i POSTTIME_{ij}$.

Replacing *INTENSITY* with *CENCITY* (role of local government within its region) or *INCOME* (economic status of a neighborhood) in Equation 13, the model can be applied to the differential impact of a natural disaster on a neighborhood with the economic status of the neighborhood and the municipality:

$$
\begin{aligned}
Y_{ij} = {} & \gamma_{00} + \gamma_{01} INCOME_i + \gamma_{10} TIME_{ij} + \gamma_{11} INCOME_i TIME_{il} \\
& + \gamma_{20} DISASTER_{ij} + \gamma_{21} CENCIY_i DISASTER_{ij} \\
& + \gamma_{30} POTTIME_{ij} + \gamma_{31} CENCITY_i POSTTIME_{ij} + \gamma_{40} NS_{ij} + \gamma_{50} NH_{ij} + \gamma_{60} M_{ij} \\
& + (\varepsilon_{ij} + \varsigma_{0i} + \varsigma_{1i} TIME_{ij} + \varsigma_{2i} DISASTER_{ij} + \varsigma_{3i} POSTTIME_{ij} + \varsigma_{4i} + \varsigma_{5i} + \varsigma_{6i}) \qquad (15)
\end{aligned}
$$

$$
\begin{aligned}
Y_{ij} = {} & \gamma_{00} + \gamma_{01} INCOME_i + \gamma_{10} TIME_{ij} + \gamma_{11} INCOME_i TIME_{il} \\
& + \gamma_{20} DISASTER_{ij} + \gamma_{21} IINCOME_i DISASTER_{ij} \\
& + \gamma_{30} POTTIME_{ij} + \gamma_{31} INCOME_i POSTTIME_{ij} + \gamma_{40} NS_{ij} + \gamma_{50} NH_{ij} + \gamma_{60} M_{ij} \\
& + (\varepsilon_{ij} + \varsigma_{0i} + \varsigma_{1i} TIME_{ij} + \varsigma_{2i} DISASTER_{ij} + \varsigma_{3i} POSTTIME_{ij} + \varsigma_{4i} + \varsigma_{5i} + \varsigma_{6i}) \qquad (16)
\end{aligned}
$$

The models of Equation 13, 14, and 15 illustrate that natural disasters change not only the slope but also the intercept, and that the degree of the changes in the slope and intercept depend on the intensity of the disaster, the economic status of the neighborhood, and the role of municipality in the metropolitan area to which the neighborhood belongs. We can decide the most appropriate model of these three models, through a comparison of the values of their deviations. The results can reveal the pattern of neighborhood change after a natural disaster and the predictors that affect the differential impact of natural disasters across neighborhoods.

4.3. Variable Descriptions and Measures

The measures of the dependent variables and the predictors are described in Table 4-3. The dependent variables for this dissertation are the four key indicators of neighborhood change: poverty (*POVERTY*), residential property values (*HOMEVALUE*), and diversity (*DIVERSITY*). Prior studies have examined the outcomes of neighborhood change, using some key indicators (see the literature review in 2.1.3. Key Outcomes of Neighborhood Change). For capturing neighborhood economic status, which is one of the key outcomes of neighborhood change, this dissertation utilizes the proportion of households below poverty level in a neighborhood (*POVERTY*). Many studies on neighborhood change have used poverty rates to track a shift in neighborhood fortunes (Galster and Mincy 1993; Galster et al. 2003) and to examine outcomes of welfare policies (e.g., Devine et al. 2003). The poverty rates represent an absolute measure of economic status of a neighborhood, which makes possible to deal with different economic status across space and time. Another variable used to assess the degree of neighborhood changes is the median home value of a neighborhood (*HOMEVALUE*). The value of housing units reflects the physical characteristics of a neighborhood. That is, an increase or decrease in property values in a neighborhood indicates a shift of physical quality of the neighborhood.

Table 4-3. Description of Variables

Variables	Description
Dependent Variable (Y_{ij}): Key Indicators of Neighborhood Change	
$POVERTY_{ij}$	Proportion of household under poverty level in census tract *i* at time *j*
$HOMEVALUE_{ij}$	Median home value of census tract *i* at time *j*
$DIVERSITY_{ij}$	Value of entropy index for various racial groups of census tract *i* at time *j*
Primary Explanatory Variables	
Time-Variant Variables at Level-1 Models	
$TIME_{ij}$	Time (1970, 1980, 1990 & 2000) for census tract *i*
$DISASTER_{ij}$	1 = Census tract *i* with experience of the first major hurricane at time *j*
$POSTTIM1_{ij}$	Number of years since the first major hurricane occurs in census tract *i* at time *j*
Time-Invariant Variables at Level-2 Models	
$INTENSITY_i$	Proportion of dollar values of damages for residential buildings to total dollar values for all residential buildings in census tract *i*
$CENCITY_i$	1 = Census tract *i* within central city in the metropolitan area
$HIGHINCOME_i$	1 = Census tract *i* with income relative to that in metropolitan area of below 1.22
$LOWINCOME_i$	1 = Census tract *i* with income relative to that in metropolitan area of below 0.70
Control Variables	
Filtering	
$NEWHOME_{ij}$	Percentage of homes 5 years or less in census tract *i* at time *j*
$OLDHOME_{ij}$	Percentage of homes 40 years or older in census tract *i* at time *j*
Social Externality	
$WHITE_{ij}$	Percentage of white population of census tract *i* at time *j*
$HISPANIC_{ij}$	Percentage of Hispanic population of census tract *i* at time *j*
$INCOME_{ij}$	Average household income of census tract *i* at time *j*
$OWNER_{ij}$	Percentage of owner-occupied homes of census tract *i* at time *j*
Political Economy	
$HIGHWAY_i$	Miles from highway to census tract *i*
CBD_i	Miles from CBD to census tract *i*
$NATURAL_i$	Miles from natural amenities (ocean or river) to census tract *i*
Metropolitan	
M_POP_i	The total population in the metropolitan area with census tract *i*
M_INCOME_i	Average household income of the metropolitan area with census tract *i*
M_UNEMP_i	Percentage of unemployment of the metropolitan area with census tract *i*
Others	
POP_{ij}	Ratio of total population in census tract *i* to that of the metropolitan area, at time *j*
$DENSITY_{ij}$	Population density of census tract *i* at time *j*
HURRICANE	Dummies for census tracts hit by each hurricane
$STATE_i$	Dummies for states that census tract *i* belongs to

Note: Some control variables may not be used according to dependent variables because of multicolinearity.

Finally, the diversity of a neighborhood (*DIVERSITY*) is utilized to estimate increasing racial disparity of the populations of different racial groups induced by natural disasters. This dissertation focuses on a change in racial segregation to investigate the diversity of neighborhood. Of many indices of neighborhood diversity, the entropy index is used here. The entropy index measures how evenly families are distributed across the various racial groups within a neighborhood. Unlike the relative measures of diversity, such as exposure index, the entropy index, as an absolute measure of diversity, can measure a variety of changes in diversity across neighborhoods and time. And unlike other absolute measures, it can easily incorporate the diversity levels of more than two groups into a single index. The most common formula for the index follows:

$$H_i = \sum_{m=1}^{M} \frac{Q_{im}}{\ln(M)}$$

where $Q_{im} = -\pi_{im} \ln(\pi_{im})$, if $\pi_{im} > 0$, Q_{im} is 0, if otherwise, π_{im} is the proportion of the population of tract *i* consisting of individuals from racial group *m* (*m*= 1, 2, 3,…., *M*) and *M* is the number of racial groups (Galster et al. 2008). Its maximum value of 1.0 means that each of groups is equally represented in
the neighborhood and its minimum value of zero denotes that only one of the groups is represented in the neighborhood. Thus, a low-entropy index indicates high segregation among racial groups within a neighborhood.

The primary explanatory variables are divided into two groups: time-variant variables of the level-1 model and time-invariant variables of the level-2 model. For the level-1 model, the observation time ($TIME_{ij}$) of this dissertation comes from the decennial data from 1970 to 2000. This variable is important, for it allows the longitudinal model to examine not only neighborhood change over time but also discontinuous neighborhood change resulting from the occurrence of a disaster. The experience of a natural disaster is represented in two ways: *DISASTER* and *POSTTIME*. The former (*DISASTER*) is a dummy variable that shows whether a census tract experiences a natural disaster at a certain time. The latter (*POSTTIME*) is the number of years since the occurrence of the natural disaster. For example, for any census tract *i* that was affected by the first hurricane in 1983, the value of the variable *DISASTER* for the census tract is 0 in 1980, and 1 in 1990 and 2000. The value of variable *POSTTIME* is 0 in 1980, 7 in 1990, and 17 in 2000.

Time-invariant variables of the level-2 model present different characteristics across the neighborhoods (in this case, census tracts), which contribute to variance in the impact of a natural disaster: the natural disaster itself, the rehabilitation efforts of the local jurisdiction, and the economic status of a neighborhood. First, the impact of a natural disaster on neighborhood change can be differential according to the intensity of the natural disaster, which affects the degree of physical damage caused by the natural disaster. This dissertation uses HAZUS-MH to differentiate the level of the severity of hurricanes among the census tracts (i.e., the treatment group) in the metropolitan counties that were affected by the five major hurricanes in the 1980s. The differential level of severity of the hurricanes among the census tracts is measured by the proportion of the dollar value of damages to residential buildings that sustained severe and complete damage from the hurricanes to the dollar value of all of the total residential buildings in each census tract.

Because of the historical event modeling function on HAZUS-MH, delineating the exact census tracts affected by a historical major natural disaster and estimating the physical damage for each census tract are both possible. HAZUS-MH calculates the likelihood that buildings in each census tract will be damaged from a major hurricane. Using the function of the wind speed of a hurricane and inventory data about the buildings such as their structural or material types, HAZUS-MH determines the probability of damage to the buildings, and based on the calculated probability, it estimates the dollar value of the damages to the buildings accounting to their occupancy types (i.e., residential, commercial, and industrial buildings) by the census tract level. The dollar value of damage for each type of buildings is estimated by five different degrees of damage: (1) no damage, (2) minor damage, (3) moderate damage, (4) severe damage, and (5) destruction. Severe damage is defined as "major window damage or roof sheathing loss, major roof cover loss, and extensive damage to interior from water" (FEMA, 2003, p.649). In other words, buildings with severe or complete damage are not structurally safe, so people who reside or work in such buildings are at risk.

The hazard literature has shown that the characteristics of a neighborhood severely affected by a natural disaster are more likely to change than those of a neighborhood only moderately or slightly affected. Severe or complete damage to residential buildings from major natural disasters are regarded as one of the main reasons why residents move out of their neighborhoods in the aftermath of a disaster and the characteristics of the neighborhoods change. Thus, this dissertation focuses on severe or complete census tract-level damage to residential buildings from the major hurricanes in the 1980s. In particular, it mainly deals with residential buildings with severe damage or destruction and estimates the differential impact of hurricanes on neighborhood change according to the intensities of the hurricanes. A independent variable, $INTENSITY_i$, represents the proportion of the dollar values of damages to residential buildings with severe damage or destruction from major hurricanes to the total dollar values for all residential buildings in the census tract $_i$. It is calculated as below;

$$INTENSITY_i = \frac{\text{\$ of Damages for Residential Buildings with Severe or Complete Damage from Major Hurricanes in Census Tract}_i}{\text{\$ of Total Residential Buildings in Census Tract}_i}$$

The total dollar value of all residential buildings in a census tract is calculated using the total number of total residential buildings and the average value of the residential buildings in the census tract. If the dollar value of damages to the residential buildings with severe or complete damage is 10% of the dollar value of all of the residential buildings, *INTENSITY* is 0.1. For the census tracts (control group) in the U.S. metropolitan counties not affected by major hurricanes, the value is 0.

Second, the extent of the rehabilitation efforts of local jurisdictions is measured in two ways: whether or not it is the central city of a metropolitan area . According to the literature, central cities and large suburban cities are more likely to receive rehabilitation funds from the federal government, and the neighborhoods in these cities are more likely to recover than those in other cities. Therefore, neighborhoods in the central city (*CENCITY*) are defined as census tracts in the central city of the surrounding metropolitan area. Other census tracts, located in relatively small suburban cities, are the base category. Finally, neighborhoods in the study area are divided into three categories according to the ratio of their average household income to the incomes of their surrounding metropolitan areas in 2000. Low-income neighborhoods (*LOWINCOME*) are defined as census tracts with relative incomes below 0.7[4]. High-income neighborhoods (*HIGHINCOME*) are characterized as census tracts with incomes relative to those of the metropolitan area above 1.22. Middle-income neighborhoods, which comprise an excluded category, include all other census tracts.

Control variables include other underlining factors that cause neighborhood change. Studies on neighborhood change theoretically and empirically divide these factors into three categories: filtering, externality, and political economy (see the literature review in 2.1.2. Theoretical Perspective on the Causes of Neighborhood Change). As discussed in the literature review, filtering is strongly related to the condition of housing stocks, particularly the ages of homes in a neighborhood; externality deals with the socioeconomic characteristics of households in neighborhoods; and political economy is associated with the location of neighborhoods. Thus, added as major control variables for estimating neighborhood change are the characteristics of housing: the percentage of new homes (*NEWHOME*) and old homes (*OLDHOME*), households (the percentage of whites (*WHITE*) and Hispanics (*HISPANIC*)), income (*INCOME*), owner-occupied homes (*OWNER*), and their locations (distance to a highway (*HIGHWAY*), the central business district (*CBD*), and natural amenities (*NATURAL*). In particular, the characteristics of a metropolitan area are controlled because the state of the metropolitan area has a direct or indirect impact on neighborhood change. The characteristics include the total population (*METRO_POP*), the average household income (*METRO_INCOME*), and the unemployment rate (*METRO_UEMP*) of the surrounding metropolitan area. In addition, other control variables include the population (*POP*) and the density (*DENSITY*)

[4] These criteria follow those that Ellen and O'Regan (2008), examining change in low-income urban neighborhoods in the United States in the 1990s, used to divide neighborhoods by income. They believed that these criteria were appropriate in the study of the historical change of neighborhoods.

of a neighborhood, dummies for each hurricane (*HURRICANE*), and dummies for the state in which a census tract is located (*STATE)* to control for differences in growth among neighborhoods, the characteristics of the hurricanes (except for intensity), and the characteristics of the states. Because of the issue of multicolinearity, these control variables will be selectively used according to the dependent variables (*POVERTY*, *HOMEVALUE*, and *DIVERSITY*).

CHAPTER 5

EMPIRICAL RESULTS

5.1. Data Selection and Descriptive Analyses

5.1.1. Data Selection

In the previous chapter, this dissertation defined the treatment group and the control group to effectively analyze the differential effects of natural disasters on neighborhood change: The treatment group is comprised of census tracts located in U.S. metropolitan counties that have been hit by five major hurricanes only in the 1980s; and the control group consists of the census tracts that are also involved in U.S. metropolitan counties that have never been affected by any major natural disasters, including hurricanes, from 1970 to 2000. As seen in Table 4-4, the numbers of the treatment and control groups are 9,419 and 25, 918, respectively. The total number of both groups is 34,867 (34,867 x 4 = 139,468 for the panel data).

The longitudinal analysis, which is used to effectively analyze the differential effects of a natural disaster, is run through a complicated computer process. Because the number of panel data (139,468) is excessive the analyses cannot be run using the SAS program. Thus, a random sample of 30% was used to effectively run the longitudinal analysis. The total number of samples which are used in this dissertation is 11,623 (out of a total number of 46,492), 3,028 of which make up the treatment group and 8,595 the control group. Figure 5-1 illustrates the sampling process and the numbers of data for each group. Of the selected samples, the hurricane that affected the largest number of census tracts is Hurricane Gloria (2,622) and the one that affected the smallest number of census tracts is Hurricane Elena (see Table 5-1).

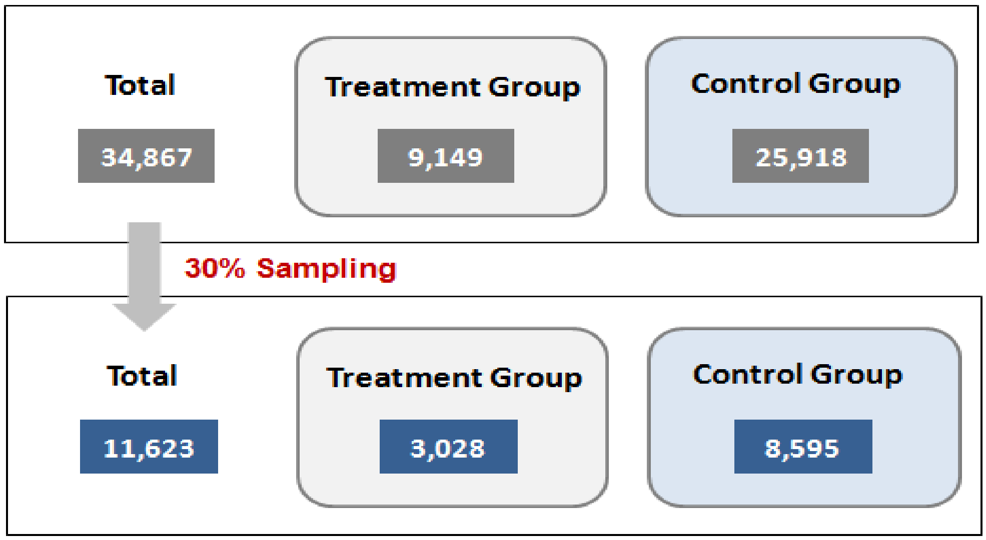


Figure 5-1. Data Selection

Table 5-1. Number of Samples for the Treatment Group, by Major Hurricanes in the 1980s

The Number of the Census Tracts Affected by Major Hurricanes only in the 1980s					
Allen	Alicia	Elena	Gloria	Hugo	Total
67	99	18	2,622	222	3,028

30% of samples

Tables 5-2 and Table 5-3 present the number of samples for the treatment group and the control group by state, respectively. The treatment group includes 16 states (Connecticut, Delaware, Los Angeles, Maine, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Virginia and West Virginia). Of the states, New York (996) had the largest number of census tracts affected by major hurricanes only in the 1980s and Virginia the smallest number. The control group includes 39 states. California (1,111) had the largest number of census numbers never affected by a major natural disaster between 1970 and 2000 and South Dakota the smallest number. Eleven states (Los Angeles, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, South Carolina, Texas, Virginia and West Virginia) include the census tracts for both the treatment and control groups.

Table 5-2. The Number of Samples for the Treatment Group by State

	The Number of Census Tracts Affected by Major Hurricanes Only in the 1980s							
State (16)	CT (244)	DE (63)	LA (14)	ME (8)	MA (370)	MS (4)	NH (24)	NJ (627)
	NY (996)	NC (109)	PA (221)	RI (71)	SC (104)	TX (166)	VA (7)	WV (9)
Total	3,028							

Table 5-3. The Number of Samples for the Control Group by State

	The Number of Census Tracts Affected by Major Hurricanes Only in the 1980s							
State (39)	AL (7)	AZ (316)	AR (99)	CA (1,111)	CO (289)	CT* (0)	DC (54)	DE* (0)
	FL (646)	GA (58)	ID (31)	IL (113)	IN (58)	KY (156)	LA* (56)	MD (369)
	ME* (0)	MA* (0)	MI (743)	MN (299)	MS* (7)	MO (158)	MT (108)	NH *(7)
	NV (141)	NJ* (21)	NM (87)	NY* (315)	NC* (7)	OH (815)	OK (149)	OR (178)
	PA* (618)	RI* (0)	SC* (60)	SD (6)	TN (279)	TX* (394)	UT (107)	VA* (199)
	WA (324)	WI (175)	WY (12)	WV* (21)				
Total	8,595							

* States includes the treatment groups, the census tracts affected by major hurricanes only in the 1980s

5.1.2. Descriptive Analyses

Table 5-4 shows the descriptive analyses for the dependent variables and main predictors used in this dissertation. The historical changes of mean (and standard deviation) from 1970 to 2000 are analyzed by dividing them into three neighborhood groups: disaster-neighborhoods, no-disaster-neighborhoods, and all neighborhoods.

In the dissertation, the first three variables in the table (POVERTY, HOMEVALUE, and DIVERSITY) are dependent variables representing the key outcomes of neighborhood change. The poverty rates (POVERTY) of all neighborhoods (including neighborhoods both with and without natural disasters experience) constantly increased during the period. For all neighborhoods, the growth rate of the poverty rates between 1970 and 2000 was 18.1 percent. The growth rate of poverty rates for neighborhoods with disaster experience (21.4%) was larger than that for neighborhoods without disaster experience (17.0%). For all of the neighborhood cases, the median home value (HOMEVALUE) rapidly increased from $15,352 in 1970 to $102,909 in 2000. The growth rate of the median home value is 19.7 percent. The difference in the growth rate of median home values of disaster-neighborhoods and that of non-disaster neighborhoods is not large (18.7% and 20.1%). In the period, neighborhoods in US metropolitan areas have been getting racially more diverse, showing a dramatic growth rate of 179 percent (from 0.15 in 1970 to 0.42 in 2000). Neighborhoods with disaster experience are more diverse in racial components compared to those without disaster experience. Figure 5-2 illustrates the historical trends of these key outcomes of neighborhood change, showing a comparison between neighborhoods with and without disaster experience.

Table 5-4. Descriptive Analysis

Variables	Neighborhood	1970		1980		1990		2000		Growth Rate 1970-2000
		Mean	St.D.	Mean	St.D.	Mean	St.D.	Mean	St.D.	
POVERTY	All	0.107	(0.10)	0.114	(0.11)	0.125	(0.13)	0.126	(0.12)	0.18
	Disaster	0.109	(0.11)	0.127	(0.13)	0.121	(0.13)	0.133	(0.13)	0.21
	Non-Disaster	0.106	(0.09)	0.109	(0.10)	0.126	(0.13)	0.124	(0.12)	0.17
HOME VALUE	All	9.639	(1.43)	10.51	(0.69)	11.16	(0.72)	11.54	(0.68)	0.20
	Disaster	9.763	(1.48)	10.32	(0.87)	11.38	(0.80)	11.59	(0.78)	0.19
	Non-Disaster	9.595	(1.41)	10.58	(0.60)	11.09	(0.68)	11.52	(0.65)	0.20
DIVERSITY	All	0.150	(0.18)	0.267	(0.23)	0.332	(0.25)	0.420	(0.26)	1.79
	Disaster	0.184	(0.21)	0.296	(0.26)	0.376	(0.27)	0.470	(0.27)	1.56
	Non-Disaster	0.138	(0.17)	0.257	(0.22)	0.316	(0.24)	0.403	(0.25)	1.92
WHITE	All	0.803	(0.35)	0.818	(0.28)	0.798	(0.27)	0.747	(0.27)	-0.07
	Disaster	0.817	(0.31)	0.788	(0.30)	0.742	(0.31)	0.684	(0.31)	-0.16
	Non-Disaster	0.799	(0.35)	0.828	(0.27)	0.817	(0.25)	0.770	(0.26)	-0.04
HISPANIC	All	0.051	(0.12)	0.065	(0.14)	0.084	(0.16)	0.117	(0.18)	1.30
	Disaster	0.064	(0.15)	0.090	(0.18)	0.115	(0.19)	0.145	(0.21)	1.27
	Non-Disaster	0.046	(0.11)	0.056	(0.12)	0.073	(0.14)	0.108	(0.17)	1.32
INCOME	All	9,867	(5,934)	20,342	(9,377)	40,270	(19,260)	56,580	(29,220)	4.73
	Disaster	10,666	(5,774)	20,975	(9,210)	44,789	(22,079)	62,737	(33,060)	4.88
	Non-Disaster	9,951	(1,769)	20,119	(9,425)	38,678	(17,894)	54,411	(27,416)	4.47
NEWHOME	All	0.151	(0.17)	0.146	(0.18)	0.111	(0.14)	0.079	(0.12)	-0.47
	Disaster	0.107	(0.14)	0.076	(0.11)	0.074	(0.10)	0.051	(0.08)	-0.52
	Non-Disaster	0.166	(0.18)	0.171	(0.19)	0.124	(0.15)	0.089	(0.13)	-0.46
OLDHOME	All	0.297	(0.29)	0.338	(0.29)	0.434	(0.30)	0.538	(0.30)	0.81
	Disaster	0.429	(0.31)	0.475	(0.30)	0.564	(0.28)	0.669	(0.26)	0.56
	Non-Disaster	0.251	(0.27)	0.290	(0.28)	0.389	(0.30)	0.492	(0.31)	0.96
METRO_ POP (1000 Person)	All	4,220	(5,99)	4,451	(6,022)	4,830	(6,314)	5,322	(6,852)	0.26
	Disaster	10,490	(8,13)	10,656	(8,089)	11,078	(8,333)	11,990	(9,047)	0.14
	Non-Disaster	2,011	(2,55)	2,265	(2,765)	2,630	(3,294)	2,973	(3,672)	0.48
METRO_ UNEMP	All	0.261	(0.21)	0.205	(0.17)	0.152	(0.17)	0.170	(0.18)	-0.35
	Disaster	0.235	(0.21)	0.215	(0.10)	0.162	(0.11)	0.216	(0.11)	-0.08
	Non-Disaster	0.270	(0.21)	0.202	(0.19)	0.148	(0.19)	0.154	(0.19)	-0.43
METRO_ INCOME	All	10,157	(1,664)	20,357	(2,591)	40,251	(6,680)	58,156	(9,110)	4.73
	Disaster	10,725	(1,155)	21,085	(1,848)	45,197	(5,881)	63,514	(7,689)	4.92
	Non-Disaster	9,951	(1,769)	20,102	(2,760)	38,509	(6,041)	56,269	(8,816)	4.65
R_POP	All	0.004	(0.01)	0.005	(0.01)	0.005	(0.01)	0.005	(0.01)	0.23
	Disaster	0.002	(0.01)	0.002	(0.01)	0.003	(0.01)	0.003	(0.01)	0.13
	Non-Disaster	0.005	(0.01)	0.006	(0.01)	0.006	(0.01)	0.006	(0.01)	0.26

Variables	Neighborhood	Mean	St.D.	**Variables**	Neighborhood	Mean	St.D.
DISASTER	Total	0.26	(0.44)	CBD	Total	0.609	(0.75)
	Disaster	1.00	(0.00)		Disaster	0.381	(0.53)
	Non-Disaster	0.00	(0.00)		Non-Disaster	0.689	(0.79)
INTENSITY	Total	0.006	(0.05)	HIGHWAY	Total	1.956	(4.74)
	Disaster	0.024	(0.10)		Disaster	1.654	(2.68)
	Non-Disaster	0	(0)		Non-Disaster	2.062	(5.28)
CCITY	Total	0.31	(0.46)	NATURE	Total	1.964	(2.60)
	Disaster	0.40	(0.49)		Disaster	0.530	(0.81)
	Non-Disaster	0.27	(0.45)		Non-Disaster	2.597	(2.85)

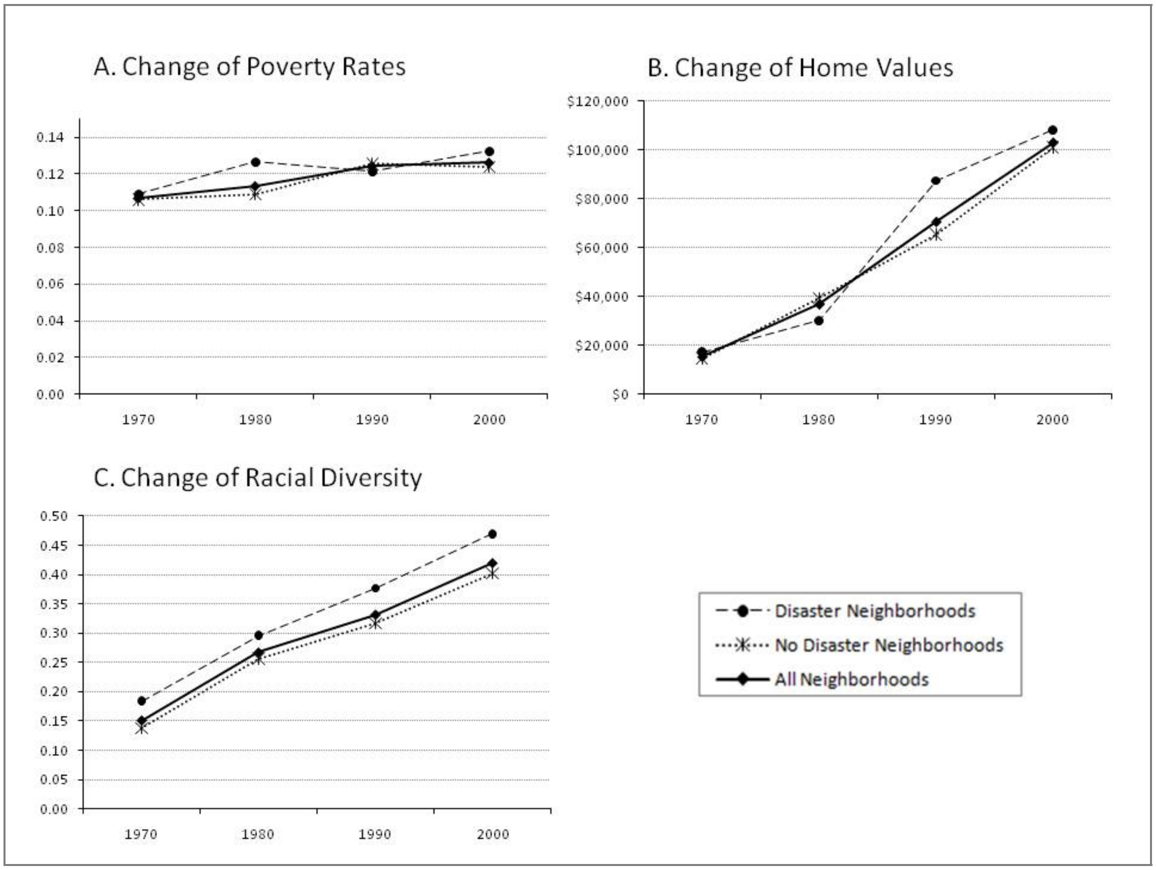
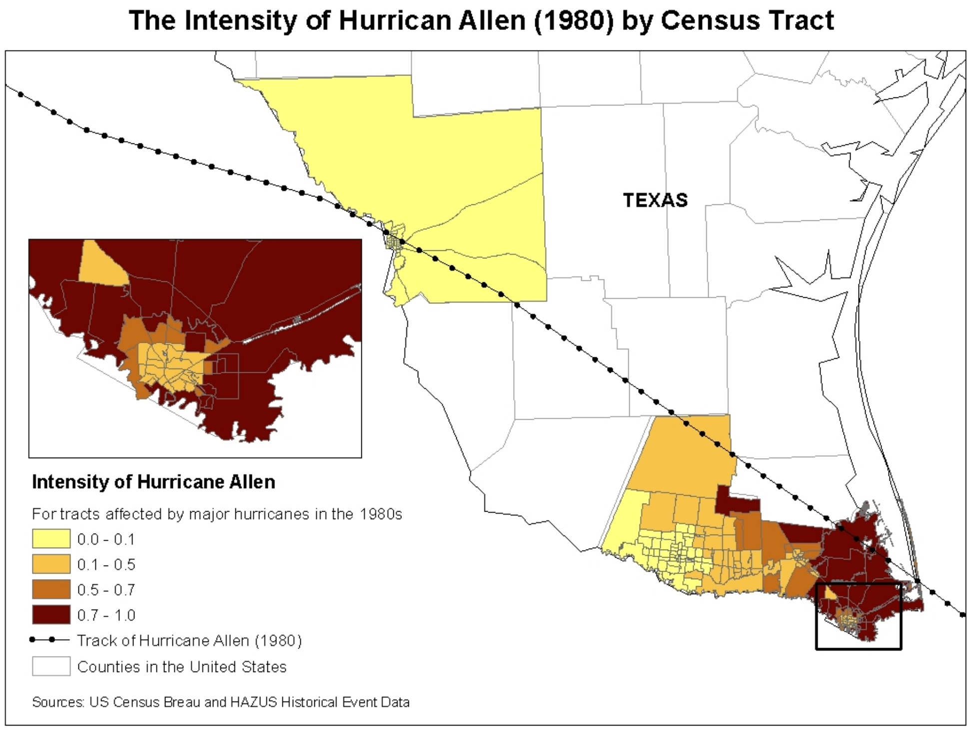


Figure 5-2. Historical Trends of Key Outcomes of Neighborhood Change (1970 to 2000)

To measure the differential effects of natural disasters on neighborhood change, this dissertation includes *INTENSITY* (intensity of disaster), *CCITY* (central city), and *INCOME* (average household income). *INTENSITY* represents the proportion of the cost of damages of residential buildings from natural disasters to the total values of all residential buildings in a neighborhood. The average proportion of disaster neighborhoods is 0.024.

Figure 5-3 illustrates the intensity of five major hurricanes in the 1980s for the census tracts affected by only the hurricanes. The intensity of Hurricane Allen was



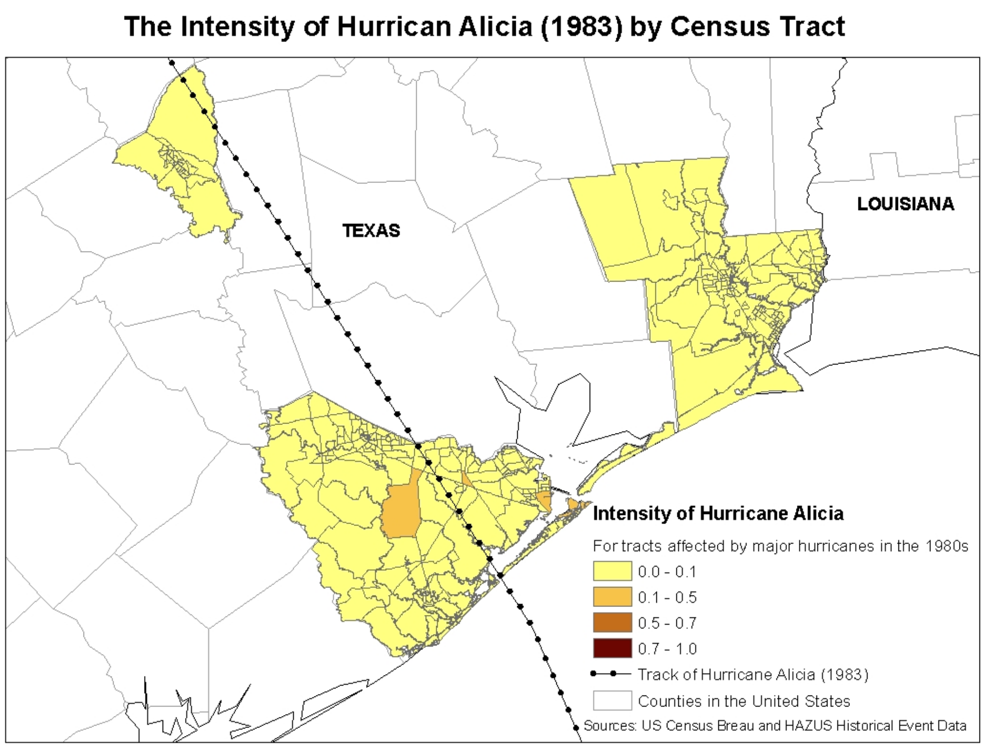
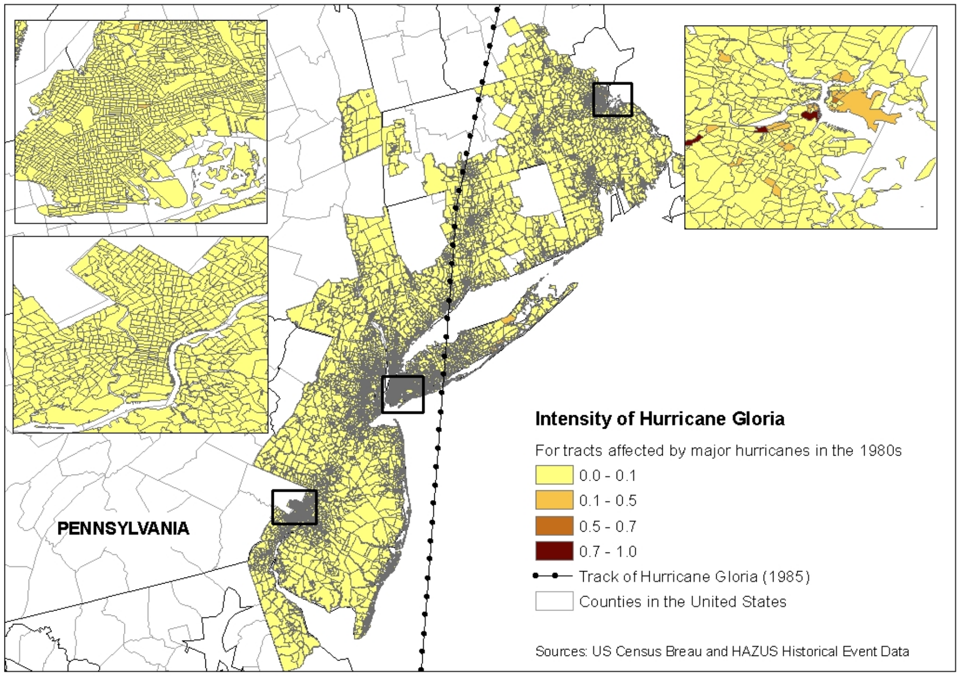


Figure 5-3. The Intensity of Major Hurricanes in the 1980s, by Census Tract

The Intensity of Hurrican Gloria (1985) by Census Tract



The Intensity of Hurrican Hugo (1989) by Census Tract

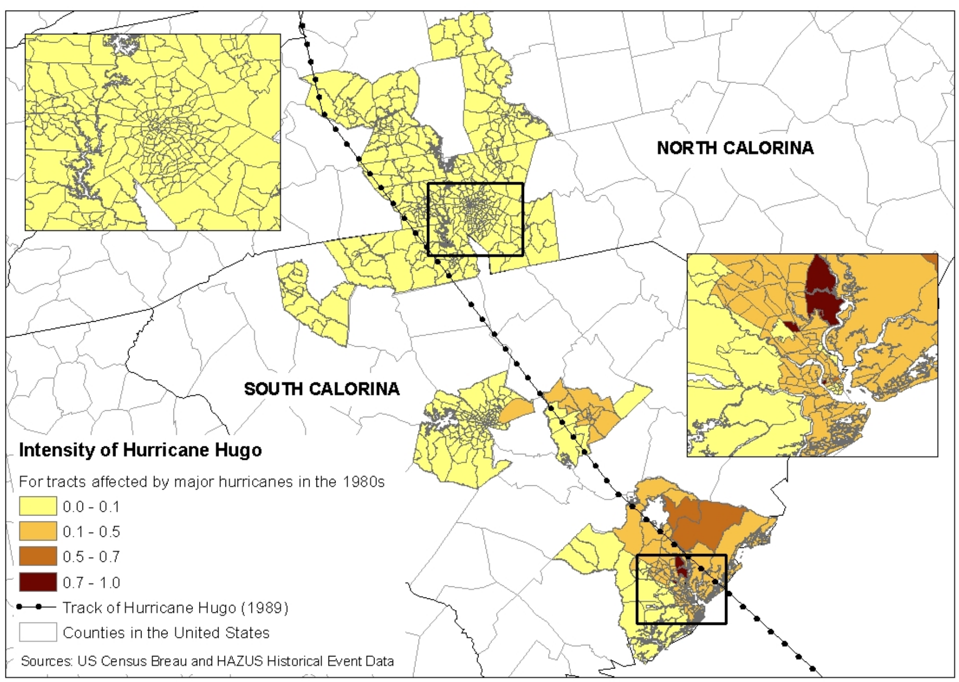


Figure 5-3. (Continued)

stronger than that of other hurricanes, so the intensity of a number of census tracts with over 0.7. About 40 percent of disaster neighborhoods were located in central cities (CCITY) while 27 percent of non-disaster neighborhoods belong to central cities. US metropolitan neighborhoods experienced a dramatic increase in their average household income (INCOME) from 1970 to 2000, showing growth rate of 473%. This increase is similar in most neighborhoods regardless of their disaster experience.

Other variables include proxies of key causes of neighborhood change, as discussed in the literature review in theoretical perspectives on the causes of neighborhood change. The variables—WHITE, HISPANIC, and INCOME—represent the social externality that explains neighborhood change. While the percentage of the white population (WHITE) of neighborhoods in metropolitan areas (-7%) slightly declined, the percentage of the Hispanic population (HISPANIC, 130%) rapidly increased during the study period. These trends occurred in both neighborhoods with and without disaster experience.

The percentage of new homes (NEWHOME) and old homes (OLDHOME) represent filtering, which explains the physical characteristics of housing units in a neighborhood. The average neighborhood experienced a decline in the proportion of new homes (-47%) and an increase in the proportion of old homes (81%). Comparing disaster neighborhoods and no-disaster-neighborhoods, we find that the proportion of new homes in disaster neighborhoods was lower than that in non-disaster-neighborhoods during all of the study times while that of old homes in disaster neighborhoods was larger.

One of main causes of neighborhood change, the political economy explains neighborhood change according to the value of investments. The location of a neighborhood is an important factor that determines its development. The distance to highway (HIGHWAY) and central business district (CBD), and natural amenities (NATURE) represent the perspective of the political economy. Disaster neighborhoods are closer to CBD (0.38 miles) and major highways (1.65 miles) and have fewer natural amenities (0.53) compared to non-disaster neighborhoods (0.69 miles, 2.06 miles, and 2.60, respectively).

Neighborhood change is strongly affected by the socioeconomic characteristics of the metropolitan area in which the neighborhoods are located. METRO_POP, METRO_UNEMP, and METRO_INCOME are the control variables for the effects of the different characteristics of metropolitan areas on neighborhood change. In general, US metropolitan areas have experienced the increases in their population and average household income and a decrease in their rates of unemployment. These trends are the same in most metropolitan areas regardless of whether or not they experienced a major disaster in the 1980s.

5.2. ANOVA and the Unconditional Growth Models

This dissertation first fit the two simpler models: the unconditional means model and the unconditional growth model. These unconditional models partition and quantify the outcome variation in two important ways: across neighborhoods without regard to time (i.e., the unconditional means model or the ANOVA model) and across both neighborhoods and time (i.e., the unconditional growth model). Their results of these models allow us to establish (1) whether neighborhood change that varies systematically is worth exploring; and (2) where the variation resides (within or between neighborhoods).

5.2.1. Home Values

5.2.1.1. The Unconditional Means Model (the ANOVA model)

The unconditional means model, also called the ANOVA model, simply describes and partitions variations in the outcomes of neighborhood change indicators. The primary purpose of the ANOVA model is to estimate these variance components, which asseses the extent of outcome on each level. If a variance component is zero, trying to predict the outcome variation at that level is pointless. That is, the amount of variation is too small to explain. If a variance component is non-zero, then some variation at that level could potentially be explained (Singer and Willet, 2003).

Model H_1 in Table 5-5 presents the results of fitting the ANOVA model to changes in home values. The fixed effect in the model, γ_{000}, estimates the grand mean ot the outcome across all occasions and neighborhoods. Rejection of its associated null hypothesis ($p < 0.001$) confirms that the average home value of the average neighborhood between 1970 and 2000 was non-zero. The next step is to examine the random effects, the major purpose for fitting this model. The estimated within-neighborhood variance, σ_ε^2 was 1.1368; the estimated between-neighborhood variance, σ_0^2 was 0.1601. Using the single parameter hypothesis test, we reject both associated null hypotheses at the .001 level. We conclude that the average neighborhood home value varied over time and that neighborhoods differed in home values. Because each variance component significantly differ from 0, linking both within-neighborhood and between-neighborhoods variation in home values to predictors is plausible.

Table 5-5. The ANOVA Model and the Unconditional Growth Model for Home Values

Home Values		The ANOVA Model (MODEL H_1)		The Unconditional Growth Model (MODEL H_2)	
Fixed Effects					
Initial Status	Intercept , γ_{000}	10.9141***	(0.0120)	9.9241***	(0.0190)
Rate of Change	TIME, γ_{100}			0.0626***	(0.0007)
Variance Components					
Level1	Within-neighborhood, σ_ε^2	1.1368***	(0.0095)	0.5969***	(0.0043)
Level2	In initial status, σ_0^2	0.1601***	(0.0080)	0.5356***	(0.0262)
	In rate of change, σ_1^2			0.00048***	(0.00004)
	Covariance, σ_{01}			-0.0125***	(0.0009)
Goodness-of-Fit					
	Deviance	128139.6		103578.0	
	AIC	128145.6		103590.0	
	BIC	128163.2		103625.2	

~ p<.10; * p<.05; **p<.01; ***p<.001

The ANOVA model serves another purpose: It allows us to evaluate numerically the relative magnitude of the within-neighborhood and between-neighborhood variance components (Bryk and Raudenbush, 1992; Singer and Willett, 2003). A useful statistic for quantifying their relative magnitude, intraclass correlation coefficient, ρ, describes the proportion of the total outcome variation that lies "between" neighborhoods. Because the total variation in Y is just the sum of the within and between-neighborhood variance components, the population intra-class correlation coefficient is

$$\rho = \frac{\sigma_0^2}{\sigma_0^2 + \sigma_\varepsilon^2}$$

We can estimate ρ by substituting the two estimated variance components from Model H0_1 into the equation. For these data, we find

$$\rho = \frac{0.1601}{0.1601 + 1.1368} = 0.123$$

indicating that about 12 percent of the total variation in home values was attributable to differences among neighborhoods. This finding indicates that 88 percent of the total variation in home values was due to within-neighborhood difference, generally caused by time.

The intra-class correlation coefficient also summarizes the size of the residual autocorrelation in the composite unconditional means model. Thus, the average correlation between any pair of composite residuals—between neighborhoods 1 and 2 or 2 and 3 or 1 and 3—is 0.12, which is quite moderate and close from the zero residual autocorrelation that an OLS analysis of these data would require. The results of the ANOVA model indicate very clear and significant variation in the home values of neighborhoods at both levels of analyses.

<u>5.2.1.2. The Unconditional Growth Model</u>

The next step is the introduction of the predictor TIME into the level-1 sub-model, as described in formula (1). Because the only predictor in this model is TIME, we consider it an unconditional growth model. Instead of postulating that the observed home values in a neighborhood during the specific time deviate by variance (ε) from its neighborhood-specific mean, it specifies that it deviates by variation (ε) from its true change trajectory. In other words, altering the level-1 specification alters what the level-1 residuals represent.

The level-1 residual variance, σ_ε^2, summarizes the scatter of the data from each neighborhood around its own change trajectory (not its neighborhood specific mean). The level-2 residual variances, σ_0^2 and σ_1^2, now summarize between-neighborhood variability in the initial status and the rates of change. Estimating these variance components allows us to distinguish level-1 variation from the two different kinds of level-2 variation and to determine whether inter-neighborhood differences in change were due to inter-neighborhood differences in the true initial status or the true rate of change.

Model H_2 in Table 5-5 presents the results of fitting the unconditional growth model to the data regarding home values. The fixed effects, γ_{000} and γ_{100}, estimate the starting point and the slope of the neighborhood average change trajectory. We reject the null hypothesis for each ($p < 0.001$), estimating that the average true change trajectory for home values has a non-zero intercept of 9.9241and a non-zero slope of +0.0626. Although the home values of the average neighborhood remained low, home values rose dramatically between 1970 and 2000, from $20,417 to $133,532.

To assess whether there is hope for future analyses-whether there is statistically significant variation in neighborhood's initial status or rate of change that level-2 predictors could explain-this dissertation examines the variance components. The level-1 residual variance, σ_ε^2, summarizes the average scatter of the observed outcome values of a neighborhood around its own true change trajectory. If the true change trajectory is linear with time, the unconditional growth model will better predict the observed outcome data than the unconditional mean model, resulting in smaller level-1 residuals and a smaller level-1 residual variance. Comparing σ_ε^2in Model H_2 to that of Model H_1, we find a decline of 0.54 (from 1.1368 to 0.5969). We conclude that 54% of the within-neighborhood variation in home values is systematically associated with linear TIME. Because we can reject the null hypothesis for this variance component in Model H_2, we also know that some important within-neighborhood variation still remains at level-1 ($p <$ 0.001), suggesting that it might be advantageous to introduce substantive predictors into the level-1 sub-model.

The level-2 variance components quantify the amount of unpredicted variation in the individual growth parameters; σ_0^2 assesses the unpredicted variability in true initial status; and σ_1^2 assesses the unpredicted variability in true rates of change. Because we reject each associated null hypothesis (at $p < 0.001$), we conclude that both true initial status and true rate of change have non-zero variability, suggesting that using level-2 predictors to explain heterogeneity in each parameter is worth trying.

The interpretation of the population covariance of the level-2 residuals, σ_{01}, according growth model, is significant. It not only assesses the relationship between the level-2 residuals but also quantifies the population covariance between the true initial status and the true change, indicating that we can assess whether the home values in neighborhoods with higher home values in 1970 increased more (or less) rapidly over time. This interpretation is easier if we re-express the covariance as a correlation coefficient, dividing it by the square root of the product of its associated variance components:

$$\rho_{01} = \frac{\sigma_{01}}{\sqrt{\sigma_0^2 \sigma_1^2}} = \frac{-0.0125}{\sqrt{(0.5356)(0.00048)}} = -0.7796$$

We conclude that the relationship between the true rate of change in home values and its level in 1970 is negative and strong, and because we cannot reject its associated null hypothesis, it is possibly zero.

5.2.1.3. The Controlled Mean Model and the Controlled Growth Model

Model H_1 (ANOVA model) in Table 5-5 showed some variation in home values not only within neighborhoods but also between neighborhoods. These variations stem from a variety of factors that can affect home values, one of the indicators of neighborhood change, as discussed in the literature review. A neighborhood has specific structural characteristics, socioeconomic characteristics, and locational amenities that determine its home values. Therefore, if we control the ANOVA model by adding variables for these characteristics, we can more accurately estimate the average home values of average neighborhoods and decrease variation among the home values. The variables include underlying factors that cause neighborhood change: filtering, externality, and political economy.

Model H_3 in Table 5-6 shows the addition of these control variables in the ANOVA model (Model H_1 in Table 5-5). Its fixed effect, γ_{000}, estimates the grand mean of the outcome, controlled by the major variables that may affect home values. It rejects its associated null hypothesis ($p < 0.001$). In the model, the average home values of the average neighborhoods are adjusted by major factors that generally affect home values. As a result, the estimated within-neighborhood variance, σ_ε^2, is 0.5722; the estimated between-neighborhood variance, σ_0^2, is 0.0760. Using the single parameter hypothesis test, we can reject both associated null hypothesis at the .001 level. Comparing σ_ε^2 and σ_0^2 of Model H_1 (the ANOVA model) in Table 5-5, both variances of Model H_3 decline by 49.7% (0.5646) and 52.5% (0.0841), respectively. That is, 12 control variables explain 50.3% of the variation within neighborhoods and 47.5% of the variation between neighborhoods. Although both variances dramatically decrease because of the control variables, each variance component significantly differ from zero. We conclude that the average neighborhood home value varied over time and that home values differed from neighborhood to neighborhood. Thus including other predictors that explain both within-neighborhood and between-neighborhood variation in home values would be advantage.

Table 5-6. The Controlled Mean Model and the Controlled Growth Model for Home Values

Home Values		The Controlled Mean Model (MODEL H_3)		The Controlled Growth Model (MODEL H_4)	
Fixed Effects					
Initial Status	Intercept γ_{000}	8.8313***	(0.1849)	8.0813***	(0.1915)
	INCOME, γ_{001}	0.00002***	(0)	0.00005***	(0)
	NEWHOME, γ_{002}	-0.0473	(0.0347)	-0.0905**	(0.0328)
	OLDHOME, γ_{003}	-0.4502***	(0.0217)	-0.2830***	(0.0207)
	WHITE, γ_{004}	0.3389***	(0.0222)	0.3153***	(0.0214)
	HISPANIC, γ_{005}	-0.5509***	(0.0410)	-0.5655***	(0.0397)
	M_POP, γ_{006}	-3.17E-9***	(0)	1.01E-8***	(0)
	M_INC, γ_{007}	0.00003***	(0)	0.00001***	(1.21E-6)
	M_UEMP, γ_{008}	-0.4311***	(0.0386)	-0.0613	(0.0386)
	R_POP, γ_{009}	17.5762***	(0.8736)	19.8091***	(0.8606)
	NATURAL, γ_{010}	0.0240***	(0.0062)	0.0251***	(0.0065)
	CBD, γ_{011}	-0.1209***	(0.0153)	-0.1518***	(0.0163)
	HIGHWAY, γ_{012}	0.0034	(0.0012)	0.0017	(0.0013)
Rate of Change	TIME, γ_{100}			0.0466***	(0.0019)
	TIME*INCOME, γ_{110}			-1.33E-6***	(0)
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.5722***	(0.0046)	0.4832***	(0.0040)
Level2	In initial status, σ_0^2	0.0760***	(0.0059)	0.1002***	(0.0064)
	In rate of change, σ_1^2			0.00007***	(6.14E-6)
Goodness-of-Fit					
	Deviance	76476.5		71903.5	
	AIC	76600.5		72033.5	
	BIC	76957.9		72408.1	

- Dummy variables for each state and each major hurricane are omitted from this table
~ p<.10; * p<.05; **p<.01; ***p<.001

Intra-class correlation coefficient, ρ, from Model H_3 is used to quantify the relative magnitude of variance between-neighborhoods to that of variance within neighborhoods. The population intra-class correlation coefficient is

$$\rho = \frac{0.0760}{0.0760 + 0.5722} = 0.117$$

It shows that about 12 percent of the total variation in home values was due to differences among neighborhoods and that 88 percent of the total variation in home values was related to within-neighborhood differences. The value of the coefficient is similar to that (0.123) of the ANOVA model.

Model H_4 in Table 5-6, used to introduce the predictor TIME and a level-2 predictor INCOME into Model H_3, accounts for the changes in the home values of a neighborhood over time and the differences in the rates of change among neighborhoods according to their socio-economic characteristics, especially income. We reject the null hypothesis for each ($p < 0.001$), estimating that the average true change trajectory for home values has a non-zero intercept of 8.8013 and a non-zero slope of +0.0466, indicating that home values tended to increase according to time; the average home values of the average neighborhood in a specific year increased by 4.6% after one year. However, because that TIME*INCOME is negative and significant at a 0.001 level, we can conclude that the higher-income the neighborhoods are, the lower the growth rates of their home values are over time.

In Model H_4, the level-1 residual variance, σ_ε^2, is 0.4832. Comparing σ_ε^2in Model H_4 to that of Model H_3, we find a decline of 0.089 (from 0.5722 to 0.4832), indicating that 8.9% of the within-neighborhood variation in home values is systematically associated with linear TIME. Comparing it to that of Model H_2 (the unconditional growth model), we also find a decline of 0.1137 (from 0.5969 to 0.4832), showing that 11.37% of the within-neighborhood variation in home values is link to the control variables, suggesting that it might be beneficial to introduce other substantive predictors into the level-1 sub-model.

The level-2 variance components, σ_0^2 and σ_1^2, asses the unpredicted variability in the true initial status and the true rates of change, respectively. From the results of Model H_4, we reject each associated null hypothesis (at $p < 0.001$), concluding that both the true initial status and the true rate of change have a non-zero variability. Thus, using other level-2 predictors may be more conductive to explaining the heterogeneity of each parameter.

5.2.2. Poverty Rates

5.2.2.1. The Unconditional Means Model (ANOVA Model)

Table 5-7 shows the results of fitting the ANOVA model and the unconditional growth model to changes in the poverty rate. In Model P_1, its fixed effect, γ_{000}, estimates the grand mean of outcome across all occasions and neighborhoods. Rejection of its associated null hypothesis ($p < 0.001$) confirms that the average poverty rate of the average neighborhoods between 1970 and 2000 was non-zero (0.1162). The estimated within-neighborhood variance, σ_ε^2 , is 0.0096; the estimated between-neighborhood variance, σ_0^2, is 0.0049. Using the single parameter hypothesis test, we can reject both associated null hypotheses at the .001 level. We can conclude that the average poverty rate of a neighborhood varies over time and that the poverty rates among neighborhoods

Table 5-7. The ANOVA Model and the Unconditional Growth Model for Poverty Rates

Poverty Rates		The ANOVA Model (MODEL P_1)		The Unconditional Growth Model (MODEL P_2)	
Fixed Effects					
Initial Status	Intercept , γ_{000}	0.1162***	(0.0016)	0.1074***	(0.0017)
Rate of Change	TIME, γ_{100}			0.0006***	(0.0001)
Variance Components					
Level1	Within-neighborhood, σ_{ε}^2	0.0096***	(0.0001)	0.0093***	(0.0001)
Level2	In initial status, σ_0^2	0.0049***	(0.0002)	0.0037***	(0.0002)
	In rate of change, σ_1^2			1.072E-6***	(0)
	Covariance, σ_{01}			0.00003***	(3.66E-6)
Goodness-of-Fit					
	Deviance	-77196.1		-77873.6	
	AIC	-77190.1		-77861.6	
	BIC	-77172.5		-77826.4	

~ p<.10; * p<.05; **p<.01; ***p<.001

differ. Because each variance component significantly differ from 0, linking both within-neighborhood and between-neighborhoods variation in poverty rate to predictors is plausible.

Intra-class correlation coefficient ρ is used to evaluate the relative magnitude of the within-neighborhood and between-neighborhood variance components numerically. We can estimate ρ by substituting the two estimated variance components from Model P_1 into the equation. For these data, we find

$$\rho = \frac{0.0049}{0.0049 + 0.0096} = 0.34$$

indicating that 34 percent of the total variation in poverty rates is attributable to differences among neighborhoods. This finding indicates that 66 percent of the total variation in poverty rates is due to within-neighborhood differences, which generally occur over time. The results of the ANOVA model clearly indicate significant variation in the poverty rates of neighborhoods on both levels of analyses.

5.2.2.2. The Unconditional Growth Model

Model P_2 in Table 5-7 presents the results of fitting the unconditional growth model to poverty rates data. The fixed effects, γ_{000} and γ_{100}, estimate the starting point and the slope of the neighborhood average change trajectory. We reject the null hypothesis for each ($p < 0.001$), estimating that the average true change trajectory for poverty rates has a non-zero intercept of 0.1074 and a non-zero slope of +0.0006. Between 1970 and 2000, the poverty rates for the average neighborhood increased from 0.1074 to 0.1254.

To assess whether level-2 predictors can explain statistically significant variation in the initial status or the level of the rate of change in a neighborhood, we examine the variance components. Comparing σ_{ε}^2, which summarizes the average scatter of the observed outcome values of a neighborhood around its own true change trajectory in Model P_2 to that in Model P_1, we find a decline of 0.0003 (from 0.0096 to 0.0093). This finding suggests that Model P_2 (the unconditional growth model) may be a more accurately predict the observed outcome data than Model P_1 (the unconditional mean model), resulting in smaller level-1 residuals and a smaller level-1 residual variance. The decline of σ_{ε}^2 indicates that 0.03% of the within-neighborhood variation in poverty rates is systematically associated with linear TIME. Because we can reject the null hypothesis for this variance component in Model P_2, we also know that some important within-neighborhood variation still remains at level-1 ($p < 0.001$), suggesting that to estimate the poverty rates of neighborhoods more effectively, substantive predictors might be introduced into the level-1 sub-model.

For the level-2 variance components, σ_0^2, to assess the unpredicted variability in the true initial status and σ_1^2, to assess the unpredicted variability in the true rates of change, we reject each associated null hypothesis (at $p < 0.001$). We conclude that both true initial status and true rate of change have a non-zero variability, suggesting that using level-2 predictors may be conductive to explaining the heterogeneity of each parameter.

The population covariance of the level -2 residuals, σ_{01}, is used to assess whether the poverty rates of neighborhoods with higher poverty rates in 1970 increased more (or less) rapidly over time. The covariance as a correlation coefficient is

$$\rho_{01} = \frac{\sigma_{01}}{\sqrt{\sigma_0^2\sigma_1^2}} = \frac{0.00003}{\sqrt{(0.0037)(0.000001)}} = 0.4932$$

We conclude that the relationship between the true rate of change in poverty rates and its level in 1970 is positive and moderate, and because we cannot reject its associated null hypothesis, it is possibly zero.

5.2.2.3. The Controlled Mean Model and the Controlled Growth Model

Model P_3 in Table 5-8 is used to add the important predictors that affect the poverty rates of neighborhoods to its ANOVA model (Model P_1 in Table 5-7) to more accurately estimate the average poverty rate of the average neighborhoods and to decrease variation in the poverty rate. Its fixed effects, from γ_{000} to γ_{012}, are used to estimate the grand mean of the outcome of poverty rates within-neighborhood and between-neighborhoods. Most of them reject their associated null hypotheses ($p < 0.001$).

Unlike its ANOVA model, the model effectively adjusts the average poverty rate of the average neighborhoods, controlled by the major factors that generally affect poverty rates. As a result, the variance components decrease; the estimated within-neighborhood variance, σ_ε^2, is 0.0048, and the estimated between-neighborhood variance, σ_0^2, is 0.0011. We can reject

Table 5-8. The Controlled Mean Model and the Controlled Growth Model for Poverty Rates

Poverty Rates		The Controlled Mean Model (MODEL P_3)		The Controlled Growth Model (MODEL P_4)	
Fixed Effects					
Initial Status	Intercept γ_{000}	0.3461***	(0.0188)	0.3766***	(0.0174)
	INCOME, γ_{001}	-1.39E-6***	(0)	-2.92E-6***	(0)
	NEWHOME, γ_{002}	-0.0277**	(0.0031)	-0.0221**	(0.0031)
	OLDHOME, γ_{003}	0.0663***	(0.0019)	0.0619***	(0.0019)
	WHITE, γ_{004}	-0.2089***	(0.0020)	-0.2080***	(0.0019)
	HISPANIC, γ_{005}	0.1845***	(0.0037)	0.1892***	(0.0036)
	M_POP, γ_{006}	-2.23E-9***	(0)	-1.11E-9***	(0)
	M_INC, γ_{007}	4.75E-6***	(0)	-1.25E-6***	(0)
	M_UEMP, γ_{008}	0.0138***	(0.0034)	4.67E-6	(0.0036)
	R_POP, γ_{009}	-0.3065***	(0.0807)	19.7639***	(0.8605)
	NATURAL, γ_{010}	-0.0009	(0.0006)	0.00002***	(0.0006)
	CBD, γ_{011}	0.0140***	(0.0016)	0.0101***	(0.0014)
	HIGHWAY, γ_{012}	-0.0004**	(0.0001)	-0.0003	(0.0001)
Rate of Change	TIME, γ_{100}			0.0019***	(0.0002)
	TIME*INCOME, γ_{110}			5.66E-8***	(0)
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.0048***	(0.00004)	0.0046***	(0.00003)
Level2	In initial status, σ_0^2	0.0011***	(0.00007)	0.0004***	(0.00006)
	In rate of change, σ_1^2			1.94E-6***	(0)
Goodness-of-Fit					
	Deviance	-84439.2		-85649.4	
	AIC	-84315.2		-85519.4	
	BIC	-83957.8		-85144.7	

- Dummy variables for each state and each major hurricane are omitted from this table
~ p<.10; * p<.05; **p<.01; ***p<.001

both associated null hypotheses at the .001 level. Comparing σ_ε^2 (0.0096) and σ_0^2 (0.0049) of Model P_1 (the ANOVA model) in Table 5-7, both variances of Model P_3 decline by 50.0% (0.0048) and 77.6% (0.0038), respectively, suggesting that 12 control variables explain 50% of the variation within neighborhood and 77.6% of the variation between neighborhoods in the poverty rates. However, each variance component is still non-zero, suggesting that the average poverty rate of a neighborhood varies over time and that the poverty rates of neighborhoods differ from those of other neighborhoods. It also suggests that including other predictors in the model better explain both within-neighborhood and between-neighborhood variation in poverty rates.

For Model P_3, intra-class correlation coefficient, ρ, which can also be estimated, is used to evaluate the relative magnitude of the within-neighborhood and between-neighborhoods variance components numerically. For these data, we find

$$\rho = \frac{0.0011}{0.0011 + 0.0048} = 0.186$$

Which shows that about 19 percent of the total variation in poverty rates is due to differences among neighborhoods and that 81 percent of the total variation in poverty rates is attributable to differences within-neighborhood. The value of the coefficient is smaller than that (0.34) of the ANOVA model (Model P_1 in Table 5-7), indicating that the control variables that represent the major causes of neighborhood change more effectively contribute to decreased variations in poverty rates among neighborhoods rather than that within a neighborhood.

Model P_4 introduces the predictor TIME and a level-2 predictor INCOME as a predictor of change into Model P_3. It supposes that the rate of change of the poverty level of neighborhoods over time differ according to the socioeconomic characteristics, particularly the income, of neighborhoods. In the model, the fixed effects, from γ_{000} to γ_{012}, estimate the starting point and γ_{100} to γ_{110} estimate the slope of the neighborhood average change trajectory. We reject the null hypothesis for each (p < 0.001, except M_UEMP and HIGHWAY) and estimate the non-zero intercept of 0.3766 and the non-zero slope of +0.0019 of the average true change trajectory for poverty rates. The level-2 predictor, TIME*INCOME, has a positive value and is significant at a 0.001 level. The results suggest that poverty rates were likely to increase over time; the average poverty rate of the average neighborhoods in a specific year gradually increased by 0.2% after one year. In addition, the model indicates that the rate of change in poverty rates grew more rapidly in the higher-income neighborhoods than in the lower-income neighborhoods.

In Model P_4, the level-1 residual variance, σ_ε^2, which expresses a variation in the poverty rates within a neighborhood is 0.0046. Comparing σ_ε^2 in Model P_4 to that of Model P_3, we find a decline of 0.0002 (from 0.0048 to 0.0046), indicating that just 0.02% of the within-neighborhood variation in poverty rates is systematically associated with linear TIME and TIME*INCOME. Comparing σ_ε^2 in Model P_4 to that of Model P_2 (the unconditional growth model), we also find a decline of 0.0047(from 0.0093 to 0.0046), showing that 0.47% of the within-neighborhood variation in poverty rates is linked to the control variables. However, there still exists variation in poverty rates within neighborhood. A better model that could explain the change in poverty rates can be made by introducing other substantive predictors into the level-1 sub-model.

The results also show that the level-2 variance components, σ_0^2 and σ_1^2, are 0.0004 and 0.000002, respectively, rejecting each associated null hypothesis (at $p < 0.001$). From these results, we can conclude that both the true initial status and the true rate of change in poverty rates have non-zero variability. That is, other level-2 predictors are necessary to more effectively decline variation in poverty rates between neighborhoods.

5.2.3. Diversity

5.2.3.1. The Unconditional Means Model (the ANOVA model)

Table 5-9 presents the results of fitting the ANOVA model and the unconditional growth model to change in the diversity. In Model D_1, the fixed effect for the diversity, γ_{000}, rejects of its associated null hypothesis ($p < 0.001$), confirming that the average diversity of the average neighborhoods between 1970 and 2000 is non-zero (0.3339). This finding indicates that the estimated grand mean of the outcome across all times and neighborhoods is 0.3339. The estimated within-neighborhood variance, σ_ε^2, is 0.0466; the estimated between-neighborhood variance, σ_0^2, is 0.0260. Both of them reject the associated null hypothesis at the .001 level. We can conclude that the diversity of the average neighborhood varies over time and that the diversity among neighborhoods differs. Because each variance component significantly differ from 0, variations in diversity both within-neighborhood and between-neighborhoods variation can be linked to the predictors.

For Model D_1, Intra-class correlation coefficient, ρ, can also be estimated to evaluate the relative magnitude of the within-neighborhood and between-neighborhoods variance components numerically. For these data, we find

Table 5-9. The ANOVA Model and the Unconditional Growth Model for Racial Diversity

Racial Diversity		The ANOVA Model (MODEL D_1)		The Unconditional Growth Model (MODEL D_2)	
Fixed Effects					
Initial Status	Intercept , γ_{000}	0.3339***	(0.0037)	0.1840***	(0.0033)
Rate of Change	TIME, γ_{100}			0.0098***	(0.0001)
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.0466***	(0.0003)	0.0344***	(0.0002)
Level2	In initial status, σ_0^2	0.0260***	(0.0010)	0.0144***	(0.0008)
	In rate of change, σ_1^2			0.00002***	(1.20E-6)
	Covariance, σ_{01}			0.00035***	(0.00002)
Goodness-of-Fit					
	Deviance	-6259.7		-18328.5	
	AIC	-6253.7		-18316.5	
	BIC	-6236.2		-18281.3	

~ p<.10; * p<.05; **p<.01; ***p<.001

$$\rho = \frac{0.0260}{0.0260 + 0.0466} = 0.36$$

indicating that 36 percent of the total variation in diversity is significantly related to differences among neighborhoods, that is, that 64 percent of the total variation in diversity is due to within-neighborhood differences. Results of the ANOVA model indicate a very clear significant variation in diversity of neighborhoods on both levels of analyses: within-neighborhood and between-neighborhood levels.

5.2.3.2. The Unconditional Growth model

Model D_2 in Table 5-9 presents the results of fitting the unconditional growth model to diversity data. The fixed effects, γ_{000} and γ_{100}, estimate the starting point and the slope of the neighborhood average change trajectory. We reject the null hypothesis for each (p < 0.001), estimating that the average true change trajectory for diversity has a non-zero intercept of 0.1840 and a non-zero slope of +0.0098. Although diversity for the average neighborhood remains low, it increases dramatically between 1970 and 2000, from 0.1840 to 0.4780.

Comparing σ_ε^2 in Model D_2 to that in Model D_1, we find a decline of 0.0122 (from 0.0466 to 0.0344). The decline of σ_ε^2 indicates that 1.22% of the within-neighborhood variation in diversity is systematically associated with linear TIME. In addition, some important within-neighborhood variation still remains at level-1 (p < 0.001), rejecting the null hypothesis for this variance component in Model D0_2. For the level-2 variance components, σ_0^2 to assess the unpredicted variability in the true initial status and σ_1^2 to assess the unpredicted variability in true rates of change, we reject each associated null hypothesis (p < 0.001). We conclude that both true initial status and the true rate of change for diversity have non-zero variability, suggesting that we may need to use level-2 predictors to explain heterogeneity in each parameter.

To assess whether the diversity rates in neighborhoods with higher diversity rates in 1970 increase more (or less) rapidly over time, the population covariance of the level -2 residuals, σ_{01}, is estimated. The covariance as a correlation coefficient is

$$\rho_{01} = \frac{\sigma_{01}}{\sqrt{\sigma_0^2\sigma_1^2}} = \frac{0.00035}{\sqrt{(0.0144)(0.00002)}} = 0.6522$$

This covariance indicates that the relationship between the true rate of change in diversity and its level in 1970 is positive and relatively strong, and because we cannot reject its associated null hypothesis, it is possibly zero.

5.2.3.3. The Controlled Mean Model and the Controlled Growth Model

In Model D_1 (ANOVA model) in Table5-9, we concluded that racial diversity showed variation not only within a neighborhood but also between neighborhoods. Model D_3 in Table 5-10 is used to add the major predictors for racial diversity in the ANOVA model. Its fixed effect, γ_{000}, which estimates the grand mean of the outcome, controlled by these major variables, is 0.5812, rejecting its associated null hypothesis (p < 0.001). In the model, the average diversity rate of the average neighborhoods is adjusted by the major factors. As a result, the estimated within-neighborhood variance, σ_ε^2, is 0.0243; and the estimated between-neighborhood variance, σ_0^2, is 0.0067. Using the single parameter hypothesis test, we can reject both associated null hypotheses at the .001 level. Compared to σ_ε^2 and σ_0^2 of Model D_1 (the ANOVA model) , both variances of Model D_3 decline by 47.9% (0.0223) and 74.2% (0.0193), respectively. That is, the major predictors of change in poverty rates explain 47.9% of the variation within neighborhood and 74.2% of the variation between neighborhoods. Although both variances are dramatically decreased because of the variables, each variance component significantly differs from zero. We conclude that racial diversity index of the average neighborhood varied over time and that neighborhoods differed in racial diversity.

In Model D_1 (ANOVA model), we concluded that racial diversity exhibited some variation not only within neighborhood but also between neighborhoods. Model D_3 is used to add the major predictors for racial diversity in the ANOVA model. Its fixed effect, γ_{000}, which estimates the grand mean of the outcome controlled by these major variables is 0.5812, rejecting its associated null hypothesis (p < 0.001). In the model, the average diversity rate of the average neighborhoods is adjusted by the major factors. As a result,

Table 5-10. The Controlled Mean Model and the Controlled Growth Model for Racial Diversity

Racial Diversity		The Controlled Mean Model (MODEL D_3)		The Controlled Growth Model (MODEL D_4)	
Fixed Effects					
Initial Status	Intercept, γ_{000}	0.5812***	(0.0444)	0.5692***	(0.0438)
	INCOME, γ_{001}	-4.86E-7***	(0)	-8E-7***	(0)
	NEWHOME, γ_{002}	0.0026	(0.0070)	0.0159*	(0.0070)
	OLDHOME, γ_{003}	0.0110**	(0.0043)	0.0127**	(0.0044)
	WHITE, γ_{004}	-0.3599***	(0.0044)	-0.3498***	(0.0044)
	HISPANIC, γ_{005}	0.6656***	(0.0083)	0.6488***	(0.0083)
	M_POP, γ_{006}	-3.33E-9***	(0)	-1.13E-9***	(0)
	M_INC, γ_{007}	-3.61E-6***	(0)	-6.7E-7***	(0)
	M_UEMP, γ_{008}	-0.0670***	(0.0077)	-0.0618***	(0.0087)
	R_POP, γ_{009}	0.0234	(0.1850)	-0.0924	(0.1830)
	NATURAL, γ_{010}	-0.0123***	(0.0015)	0.0102***	(0.0015)
	CBD, γ_{011}	-0.0240***	(0.0037)	-0.0300***	(0.0037)
	HIGHWAY, γ_{012}	-0.0017***	(0.0003)	-0.0019***	(0.0003)
Rate of Change	TIME, γ_{100}			0.0081***	(0.0004)
	TIME*INCOME, γ_{110}			3.32E-9***	(0)
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.0243***	(0.0002)	0.0233***	(0.0002)
Level2	In initial status, σ_0^2	0.0067***	(0.0004)	0.0055***	(0.0004)
	In rate of change, σ_1^2			5.51E-6***	(0)
Goodness-of-Fit					
	Deviance	-28061.7		-28933.6	
	AIC	-27937.7		-28803.6	
	BIC	-27580.4		-28429.0	

- Dummy variables for each state and each major hurricane are omitted from this table
~ p<.10; * p<.05; **p<.01; ***p<.001

the estimated within-neighborhood variance, σ_ε^2, is 0.0243; and the estimated between-neighborhood variance, σ_0^2, is 0.0067. Using the single parameter hypothesis test, we can reject both associated null hypotheses at the .001 level. Compared to σ_ε^2 and σ_0^2 of Model D_1 (the ANOVA model), both variances of Model D_3 decline by 47.9% (0.0223) and 74.2% (0.0193), respectively. That is, the major predictors of change in poverty rates explain 47.9% of the variation within neighborhood and 74.2% of the variation between neighborhoods. Although both variances dramatically decreased because of the variables, each variance component significantly differ from zero. We conclude that racial diversity index of the average neighborhood varies over time and that neighborhoods differ in racial diversity.

In Model D_3, intra-class correlation coefficient ρ is

$$\rho = \frac{0.0067}{0.0067 + 0.0243} = 0.216$$

indicating that about 22 percent of the total variation in the diversity index is associated with differences among neighborhoods and that 88 percent of the total variation in home values is related to differences within-neighborhood. The value of the intra-class correlation coefficient is smaller than that (0.36) for Model D_1. Thus, we can say that the control variables more effectively explain variation in racial diversity between neighborhoods, rather than variation within neighborhood.

Model D_4 considers time a key factor of change in racial diversity. We estimate that the average true change trajectory for home values has a non-zero intercept of 0.5692 and a non-zero slope of +0.0081, rejecting the null hypothesis for each (p < 0.001) indicating that the racial diversity of neighborhoods tends to increase over time; and the average racial diversity of the average neighborhood in a specific year increases by 0.81% after one year. TIME*INCOME is also positive and significant at 0.001 level. We can conclude that higher-income neighborhoods were more likely to experience rapid growth in the racial diversity over time than lower-income neighborhoods.

In Model D_4, the level-1 residual variance, σ_ε^2, which represents variation within neighborhood, is 0.0233. Compared to σ_ε^2 of Model D_3, we find a decline of 0.0010, indicating that TIME explains 0.1% of the variation in racial diversity within-neighborhood variation. Comparing σ_ε^2 of Model D_2 (the unconditional growth model), we also find a decline of 0.0111 (from 0.0344 to 0.0233), showing that 1.11% of within-neighborhood variation in racial diversity is linked to the control variables. However, some variation within neighborhoods still cannot be explained by time or 12 control variables. Thus, other substantive predictors could be introduced into the level-1 sub-model. From the result of Model D_4, we also estimate the level-2 variance components, σ_0^2 and σ_1^2, rejecting each associated null hypothesis (at $p < 0.001$), indicating non-zero variability in both the true initial status and the true rate of change.

5.3. The Effects of Natural Disasters on Neighborhood Change

5.3.1. Home Values

Table 5-11 shows the result of the analysis for a discontinuous model for the change in home values, affected by a major disaster. From the previous analyses, we understand that home values tend to increase over time and the rate of the increase tends to be larger in relatively lower-income neighborhoods than in higher-income neighborhoods.

In the trajectory of home values, home values in neighborhoods' home values change in two ways as a result of a DISASTER experience: They abruptly rise (or decline), and their subsequent rate of change increases (or decreases) (see Model C in Figure 4-3). This finding suggests that both the elevation and the slope of the level-1

Table 5-11. The Effects of Natural Disasters on Neighborhood Home Values

Home Values		The Controlled Growth Model (MODEL H_4)		MODEL H_5	
Fixed Effects					
Initial Status	Intercept, γ_{000}	8.0813***	(0.1915)	8.0903***	(0.1907)
	INCOME, γ_{001}	0.00005***	(0)	0.00005***	(0)
	NEWHOME, γ_{002}	-0.0905**	(0.0328)	-0.0952**	(0.0329)
	OLDHOME, γ_{003}	-0.2830***	(0.0207)	-0.2807***	(0.0208)
	WHITE, γ_{004}	0.3153***	(0.0214)	0.3173***	(0.0209)
	HISPANIC, γ_{005}	-0.5655***	(0.0397)	-0.5645***	(0.0397)
	M_POP, γ_{006}	1.01E-8***	(0)	1.06E-8***	(0)
	M_INC, γ_{007}	0.00001***	(1.21E-6)	8.60E-6***	(1.3E-6)
	M_UEMP, γ_{008}	-0.0613	(0.0386)	-0.0629	(0.0386)
	R_POP, γ_{009}	19.8091***	(0.8606)	19.6261***	(0.8590)
	NATURAL, γ_{010}	0.0251***	(0.0065)	0.0260***	(0.0065)
	CBD, γ_{011}	-0.1518***	(0.0163)	-0.1532***	(0.0162)
	HIGHWAY, γ_{012}	0.0017	(0.0013)	0.0015	(0.0013)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}			**-0.0766***	(0.0335)
Rate of Change	TIME, γ_{100}	0.0466***	(0.0019)	0.0490***	(0.0020)
	TIME*INCOME, γ_{110}	-1.33E-6***	(0)	-1.32E-6***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}			**0.0026**	(0.0024)
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.4832***	(0.0040)	0.4820***	(0.0040)
Level2	In initial status, σ_0^2	0.1002***	(0.0064)	0.0998***	(0.0059)
	In rate of change, σ_1^2	0.00007***	(6.14E-6)	0.00006***	(6.44E-6)
	In DISASTER, σ_2^2			0.0354***	(0.0084)
	In POSTTIME, σ_3^2			0.00001	(0.00003)
Goodness-of-Fit					
	Deviance	71903.5		71849.3	
	AIC	72033.5		71987.3	
	BIC	72408.1		72385.0	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.1. Model Output for MODLE H_5 on Appendix)

~ p<.10; * p<.05; **p<.01; ***p<.001

trajectory differ in both the pre- and post-DISASTER experiences. Model H_5 in Table 5-11 shows these discontinuities in the elevation and the slope by including fixed and random effects for DISASTER and POSTTIME. As a result of the analysis, the DISASTER predictor has a significant negative effect on neighborhood home values at a 95% confidence level, with a value of -0.0766. However, the POSTTIME predictor is positive (0.0026) and statistically insignificant at the conventional level. It appears as if the price of homes in the neighborhoods that experienced the major disaster immediately decreased by 7.66 percent relative to comparable homes in the non-disaster neighborhoods; however that the slope pre- and post-DISASTER experiences in average neighborhoods may be not differ.

If we compare the variation component within neighborhood (σ_ε^2) of Model H_5 (0.4820) to that of Model H_4 (0.4832) in Table 5-6, we can assess the explanatory power of the DISASTER predictor. The difference in this variance component between both models is 0.0011. Relative to the size of Model H_4 variance components, this difference shows a reduction of 0.0019 (0.0011/0.4832). We conclude that DISASTER explains 0.19 percent of the variance in home values within a neighborhood.

Figure 5-4 represents the results of Model H_5, the changes in historical neighborhood trend for home values caused by a natural disaster. The estimated home values of the average neighborhoods in 1970 and 1980 were $7,094 and $16,435, respectively. If an average neighborhood was hit by a major hurricane in 1985, the estimated home values immediately decreased by $1,961 ($24,636), compared to that of other neighborhoods ($26,597) that were not affected by the hurricane. Although the gap between the home values of disaster-neighborhoods and those of no-disaster-neighborhoods may not have further widened, the drop in home values after a natural disaster did not recovered for a long time after that disaster.

The variance components between neighborhoods σ_0^2 and σ_1^2, compared with those in Model H_4, change: The relative change of σ_0^2 is (0.1002-0.0998)/0.1002 = 0.004, and the relative change of σ_1^2 is (0.00007-0.00006)/0.00007 = 0.143. These changes suggest that σ_0^2 and σ_1^2 decline by about 0.4 % and 14.3% from those of Model H_4, respectively, remaining significant at a 99% confidence level. That is, the disaster predictors (DISASTER and POSTTIME) explain the 0.4 percent of between-neighborhood variability in the initial status and the 14.3 percent of between-neighborhoods variability in the rates of change for the home value trajectory.

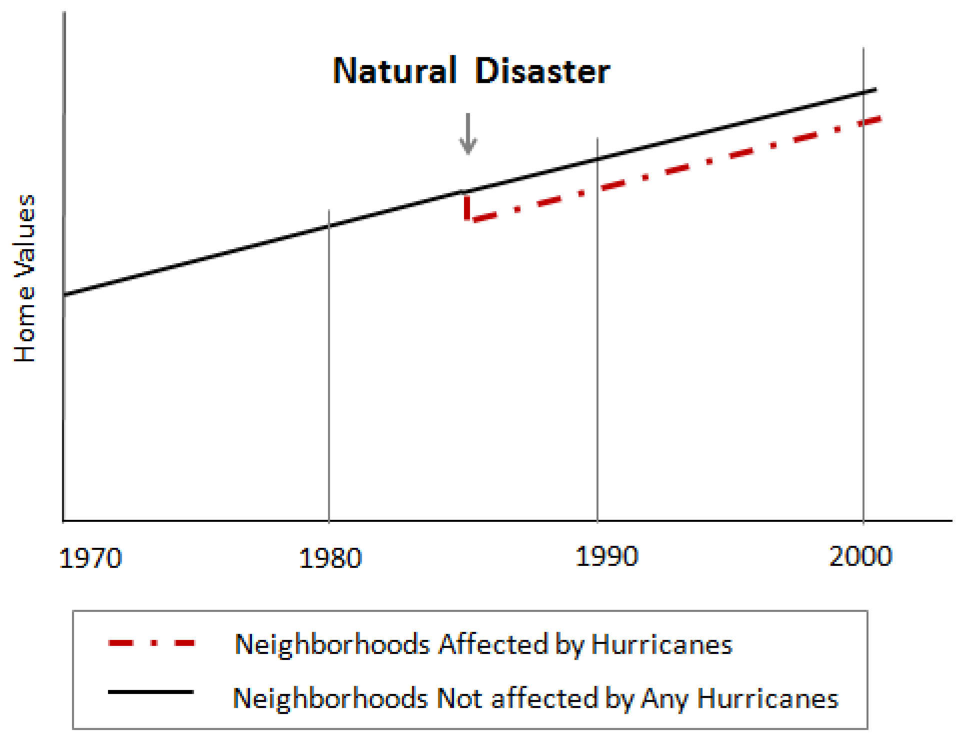


Figure 5-4. The Effects of Natural Disasters on Neighborhood Home Values

The variance component in discontinuity in elevation for DISASTER between neighborhoods, σ_2^2, is 0.0354 and statistically significant at a 99% confidence level, indicating that potentially explicable residual variations in fixed effects remain. That is, the degree of discontinuity in elevation for DISASTER differs among neighborhoods. We conclude that we should explore the effects of other level-2 predictors because it could help explain some of the DISASTER residual variation. On the other hand, the variance component in the discontinuity in the rate of change for POSTTIME between neighborhoods, σ_3^2, is 0.0026, but it is not statistically significant at a conventional level. Therefore, we cannot presume variability in the rate of change in home values between neighborhoods after a disaster.

5.3.2. POVERTY RATES

Table 5-12 represents the results of three discontinuous models for changes in the poverty rates of neighborhoods interrupted by the major disaster. In the model, most of variables that may affect the initial status of poverty rates, except the metropolitan unemployment rate and the natural amenity index, are significant at a conventional level with the expected signs. From 1970 to 2000, the poverty rates of neighborhoods in the metropolitan areas tended to increase over time and the rate of the increase was more likely to be large in the relatively higher-income neighborhoods than in the lower-income neighborhoods.

Model P_5 shows these discontinuities in elevation and in the slope by including fixed and random effects for DISASTER and POSTTIME. The model shows that both the elevation and the slope of the level-1 trajectory differ both before and after the

Table 5-12. The Effects of Natural Disasters on Neighborhood Poverty Rates

Poverty Rates		The Controlled Growth Model (MODEL P_4)		MODEL P_5	
Fixed Effects					
Initial Status	Intercept, γ_{000}	0.3766***	(0.0174)	0.3811***	(0.0173)
	INCOME, γ_{001}	-2.92E-6***	(0)	-3.24E-6***	(0)
	NEWHOME, γ_{002}	-0.0221**	(0.0031)	-0.0214***	(0.0031)
	OLDHOME, γ_{003}	0.0619***	(0.0019)	0.0613***	(0.0019)
	WHITE, γ_{004}	-0.2080***	(0.0019)	-0.2071***	(0.0019)
	HISPANIC, γ_{005}	0.1892***	(0.0036)	0.1882***	(0.0036)
	M_POP, γ_{006}	-1.11E-9***	(0)	-736E-12***	(0)
	M_INC, γ_{007}	-1.25E-6***	(0)	-1.66E-6***	(0)
	M_UEMP, γ_{008}	4.67E-6	(0.0036)	0.0015	(0.0036)
	R_POP, γ_{009}	19.7639***	(0.8605)	-0.2799***	(0.0766)
	NATURAL, γ_{010}	0.00002***	(0.0006)	0.0002	(0.0006)
	CBD, γ_{011}	0.0101***	(0.0014)	0.0093***	(0.0014)
	HIGHWAY, γ_{012}	-0.0003	(0.0001)	-0.0003**	(0.0001)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}			**0.0316***	(0.0031)
Rate of Change	TIME, γ_{100}	0.0019***	(0.0002)	0.0024***	(0.0002)
	TIME*INCOME, γ_{110}	5.66E-8***	(0)	6.82E-8***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}			**-0.0017***	(0.0002)
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.0046***	(0.00003)	0.0046***	(0.0001)
Level2	In initial status, σ_0^2	0.0004***	(0.00006)	0.0004***	(0.0001)
	In rate of change, σ_1^2	1.94E-6***	(0)	2.01E-6***	(0)
	In DISASTER, σ_2^2			**0.000197****	(0)
	In POSTTIME, σ_3^2			**0*****	(0)
Goodness-of-Fit					
	Deviance	-85649.4		-85774.9	
	AIC	-85519.4		-85638.9	
	BIC	-85144.7		-85246.9	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.2. Model Output for MODLE P_5 on Appendix)
~ p<.10; * p<.05; **p<.01; ***p<.001

DISASTER experience. As a result of the analysis, the DISASTER predictor has a significant positive effect on the poverty rates of neighborhoods at a 99.9% confidence level with a value of 0.0316; and the POSTTIME predictor is negative (-0.0017) and statistically significant at a 99.9% confidence level. It is likely that the poverty rates of the neighborhoods that experience a major disaster immediately increase by 0.0316 to comparable non-disaster neighborhoods and that the slope before and after the DISASTER experience of average neighborhoods differ, decreasing by 0.0017, suggesting that neighborhoods with disaster experience could take about 18.6 years to return to the same level of poverty as neighborhoods without disaster experience.

Figure 5-5 illustrates the results of Model P_5, changes in the historical neighborhood trend in poverty rates caused by a natural disaster. The estimated poverty rates of the average neighborhoods in 1970 and 1980 are 0.104 and 0.18, respectively. If the average neighborhoods were hit by a major hurricane in 1985, its estimated poverty rate immediately increased by 0.0316 (0.20) compared to that of other neighborhoods (0.17) not affected by the hurricane. Although poverty rates of disaster-neighborhoods and those of no-disaster-neighborhoods still differ in 2000, the difference decreases over time. The difference is 0.023 in 1990 and 0.015 in 2000.

Comparing the variation component within neighborhood (σ_ε^2) of Model P_5 (0.0046) to that of Model P_4 (0.0046), the difference between this variance component is 0, which indicates that DISASTER might not have affected the variance in poverty rates within neighborhoods. The variance components of neighborhoods, σ_0^2 and σ_1^2, are 0.0004 and 0.000002, respectively. The difference between σ_0^2 of both models is zero and that of σ_1^2 is very small (0.00000007), and the remaining significance at the 99.9% confidence level. That is, the two predictors regarding major disaster (DISASTER and POSTTIME) are not likely to explain the variability in the initial status between neighborhoods, and they are likely to explain only light variability in that of between-neighborhoods in the rates of change for the trajectory of poverty rate change.

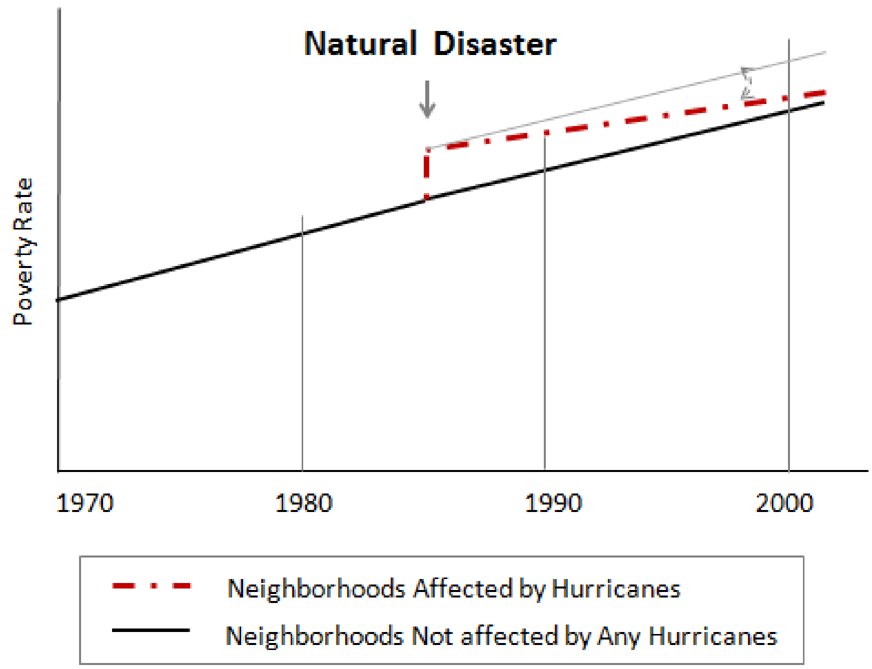


Figure 5-5. The Effects of Natural Disasters on Neighborhood Poverty Rate

The variance component in discontinuity in elevation for DISASTER between neighborhoods, σ_2^2, is about 0.0002 and statistically significant at a 99% confidence level, indicating that potentially explicable residual variations in the fixed effects are small but still remain. That is, the degree of the discontinuity in elevation for DISASTER among neighborhoods differs. On the other hand, the variance component in discontinuity in the rate of change for POSTTIME between neighborhoods, σ_3^2, is 0 and statistically significant at a 99.9% level. Thus, we can conclude that the rate of change in poverty rates between neighborhoods after a disaster show no variability.

5.3.3. Racial Diversity

Table 5-13 presents the results of the analysis for a discontinuous model for the change in diversity by the major disaster. Racial diversity tends to increase over time, and the rate of the increase is more likely to accelerate in relatively higher-income neighborhoods than in lower-income neighborhoods. Model D_5 shows discontinuities in the elevation and in the slope of the neighborhood racial diversity trajectory, including fixed and random effects for DISASTER and POSTTIME. As a result of the analysis, the DISASTER predictor has a negative effect (-0.0095) on neighborhood racial diversity, but it is not statistically significant on the conventional level. The POSTTIME predictor is also negative (-0.00047) and statistically insignificant on the conventional level.

Comparing those of Model D_4, the three variance components, σ_ε^2, σ_0^2 and σ_1^2, of Model D_5 do not largely differ. We understand that the two predictors related to major disasters (DISASTER and POSTTIME) do not explain not only within-neighborhood variability but also between-neighborhood variability in racial diversity.

The variance component in discontinuity in elevation for DISASTER between neighborhoods, σ_2^2, is 0.00029 and not statistically significant on the conventional level, indicating that potentially explicable residual variations in the fixed effects might not remain. That is, the degree of discontinuity in the elevation for DISASTER among neighborhoods is not likely to differ. On the other hand, the variance component in discontinuity in the rate of change for POSTTIME between neighborhoods, σ_3^2, is small but statistically significant at a 90% confidence level. Therefore, we can say that the rate of change in racial diversity between neighborhoods after a disaster exhibits some variability, but it is very small.

Table 5-13. The Effects of Natural Disasters on Neighborhood Racial Diversity

Racial Diversity		The Controlled Growth Model (MODEL D_4)		MODEL D_5	
Fixed Effects					
Initial Status	Intercept, γ_{000}	0.5692***	(0.0438)	0.5656***	(0.0438)
	INCOME, γ_{001}	-8E-7***	(0)	-7.74E-7***	(0)
	NEWHOME, γ_{002}	0.0159*	(0.0070)	0.0168**	(0.0071)
	OLDHOME, γ_{003}	0.0127**	(0.0044)	0.0130**	(0.0044)
	WHITE, γ_{004}	-0.3498***	(0.0044)	-0.3496***	(0.0044)
	HISPANIC, γ_{005}	0.6488***	(0.0083)	0.6484***	(0.0083)
	M_POP, γ_{006}	-1.13E-9***	(0)	-1.31E-9***	(0)
	M_INC, γ_{007}	-6.7E-7***	(0)	-4.26E-7***	(0)
	M_UEMP, γ_{008}	-0.0618***	(0.0087)	-0.0606***	(0.0087)
	R_POP, γ_{009}	-0.0924	(0.1830)	-0.0858	(0.1829)
	NATURAL, γ_{010}	0.0102***	(0.0015)	-0.0103***	(0.0015)
	CBD, γ_{011}	-0.0300***	(0.0037)	-0.0297***	(0.0037)
	HIGHWAY, γ_{012}	-0.0019***	(0.0003)	-0.0019***	(0.0003)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}			**-0.0095**	(0.0065)
Rate of Change	TIME, γ_{100}	0.0081***	(0.0004)	0.0079***	(0.0005)
	TIME*INCOME, γ_{110}	3.32E-9***	(0)	2.27E-9***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}			**-0.00047**	(0.0005)
Variance Components					
Level1	Within-neighborhood, σ_e^2	0.0233***	(0.0002)	0.0233***	(0.0002)
Level2	In initial status, σ_0^2	0.0055***	(0.0004)	0.0055***	(0.0004)
	In rate of change, σ_1^2	5.51E-6***	(0)	5.45E-6***	(0)
	In DISASTER, σ_2^2			0.00029	(0.0003)
	In POSTTIME, σ_3^2			3.061E-6~	(2.04E-6)
Goodness-of-Fit					
	Deviance	-28933.6		-28946.1	
	AIC	-28803.6		-28808.1	
	BIC	-28429.0		-28410.3	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.3. Model Output for MODLE D_5 on Appendix)

~ p<.10; * p<.05; **p<.01; ***p<.001

5.4. The Differential Effects of Disaster on Neighborhood Change

This dissertation explores the connection between natural disasters and neighborhood change. From the results of the previous longitudinal data analyses, we understand that natural disasters are likely to affect trends in changes in the home values, the poverty rates, and the racial diversity. In particular, neighborhood home values tend to instantly change in their elevation of their trajectory, but not to change in their subsequent rate of change after the major natural disasters hit. Neighborhoods are likely to experience discontinuity in not only the elevation, but also the slope of the poverty rate trajectory by natural disasters. However, although natural disasters are not likely to affect the racial diversity of the average neighborhood in the elevation or the change of rate, the variance component in discontinuity in the rate of change between neighborhoods still exists, which suggests that the rate of change in racial diversity between neighborhoods after a disaster still exhibits variability.

As a next step, this dissertation examines whether the effects of natural disasters on the neighborhood change trajectory differ among neighborhoods. This dissertation supposes that natural disasters affect trends in neighborhood change differently according to (1) the magnitude of the natural disasters, (2) the socioeconomic conditions of a neighborhood, and (3) the political power of the local jurisdiction to which a neighborhood belongs. In the following section, we examine these hypotheses using the longitudinal data analyses.

5.4.1. The Intensity of a Disaster

5.4.1.1. The Differential Effects of Disasters on Neighborhood Home Values According to the Intensity of the Natural Disasters

Table 5-14 shows the results of the analyses for the differential effects of natural disasters on the changes in the home values of a neighborhood according to the magnitude of the disasters. Model H_6 includes INTENSITY as a predictor of the initial status of the neighborhood home value trajectory. INTENSITY presents the differential effects of disasters on change in home values according to the magnitude of the disasters. In the model, most of the variables that may affect the initial status of home values are significant with the expected signs. The interpretation of its three fixed effects is straightforward: (1) The estimated initial HOMEVALUE for the average neighborhoods without the experience of a major natural disaster is 8.088 ($p < .001$); (2) the estimated differential in initial HOMEVALUE between neighborhoods with and without a disaster experience is -0.0531 (but it is not statistically significant on the conventional confidence level); (3) the estimated differential in initial HOMEVALUE according to the intensity of a disaster is -1.2079 ($p < .01$); (4) the estimated rate of change in HOMEVALUE for the average neighborhoods without the experience of a major natural disaster is 0.0491 ($p < .001$); (5) the estimated differential in the rate of change in HOMEVALUE between neighborhoods with a disaster experience and the others is 0.0010 (not statistically significant); and (6) in neighborhoods with disaster experience, the estimated differential in the rate of change in HOMEVALUE between neighborhoods with an intensity of 0 and those with an intensity of 1 is 0.1245 ($p < .05$).

Table 5-14. The Differential Effect of Natural Disasters on Neighborhood Home Values According to the Intensity of Natural Disasters

Home Values		MODEL H_5		MODEL H_6	
Fixed Effects					
Initial Status	Intercept, γ_{000}	8.0903***	(0.1907)	8.0882***	(0.1905)
	INCOME, γ_{001}	0.00005***	(0)	0.00005***	(0)
	NEWHOME, γ_{002}	-0.0952**	(0.0329)	-0.0939**	(0.0329)
	OLDHOME, γ_{003}	-0.2807***	(0.0208)	-0.2789***	(0.0208)
	WHITE, γ_{004}	0.3173***	(0.0209)	0.3189***	(0.0209)
	HISPANIC, γ_{005}	-0.5645***	(0.0397)	-0.5623***	(0.0397)
	M_POP, γ_{006}	1.06E-8***	(0)	1.07E-8***	(0)
	M_INC, γ_{007}	8.60E-6***	(1.3E-6)	8.50E-6***	(1.3E-6)
	M_UEMP, γ_{008}	-0.0629	(0.0386)	-0.0626~	(0.0382)
	R_POP, γ_{009}	19.6261***	(0.8590)	19.624***	(0.8581)
	NATURAL, γ_{010}	0.0260***	(0.0065)	0.0261***	(0.0064)
	CBD, γ_{011}	-0.1532***	(0.0162)	-0.1532***	(0.0162)
	HIGHWAY, γ_{012}	0.0015	(0.0013)	0.0015	(0.0013)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}	**-0.0766***	(0.0335)	**-0.0531**	(0.0347)
	DISASTER* INTENS, γ_{014}			**-1.2079****	(0.4583)
Rate of Change	TIME, γ_{100}	0.0490***	(0.0020)	0.0491***	(0.0020)
	TIME*INCOME, γ_{110}	-1.32E-6***	(0)	-1.32E-6***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}	**0.0026**	(0.0024)	**0.0010**	(0.0024)
	POSTTIME*INTENS, γ_{130}			**0.1245***	(0.0517)
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.4820***	(0.0040)	0.4808***	(0.0040)
Level2	In initial status, σ_0^2	0.0998***	(0.0059)	0.0996***	(0.0064)
	In rate of change, σ_1^2	0.00006***	(6.44E-6)	0.00006***	(6.5E-6)
	In DISASTER, σ_2^2	0.0354***	(0.0084)	0.0362***	(0.0085)
	In POSTTIME, σ_3^2	0.00001	(0.00003)	0.00001	(0.00003)
Goodness-of-Fit					
	Deviance	71849.3		71714.1	
	AIC	71987.3		71856.1	
	BIC	72385.0		72265.3	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.4. Model Output for MODLE H_6 on Appendix)

~ p<.10; * p<.05; **p<.01; ***p<.001

The results of the model suggest that although a natural disaster experiences itself is not likely to cause an instant decline in neighborhood home values, the intensity of a natural disaster is likely to result in a sharply instant decrease in home values. This finding suggests that neighborhoods with a more severe disaster experience tend to suffer from more a rapid decline in their home values than those with a less severe disaster experience. However, the former tend to experience more rapid annual increase in home values following the decrease that occurred immediately after the natural disaster.

Figure 5-6 represents the results of Model H_6, the differential effects of major hurricanes in the 1980s on neighborhood home value according to the intensity of the hurricanes. The estimated home values of the average neighborhoods in 1970 and 1980 are $7,091 and $16,432, respectively. If the average neighborhoods were hit by a major hurricane with an intensity of 0.3 and 0.5 in 1985, their estimated home values immediately decreased by $8,080 ($18,502) and $12,051 ($14,531), respectively, compared to those of other neighborhoods ($26,581) that were not affected by the hurricane. Although the gap between the home values of disaster neighborhoods and no-disaster neighborhoods did not widen, the home values that dropped following the natural disasters took a long time after the disaster to recover. However, the home values of neighborhoods with sever disaster experience are likely to recover more rapidly than those without such experience. As a result, in 2000, fifteen years after the hurricane hit, the home values of neighborhoods that experienced a disaster experience of 0.1 intensity were similar to those of neighborhood that had no such experience. Surprisingly, the home values of neighborhoods that experienced a disaster of 0.5 intensity were higher than those of neighborhoods that had no such experience.

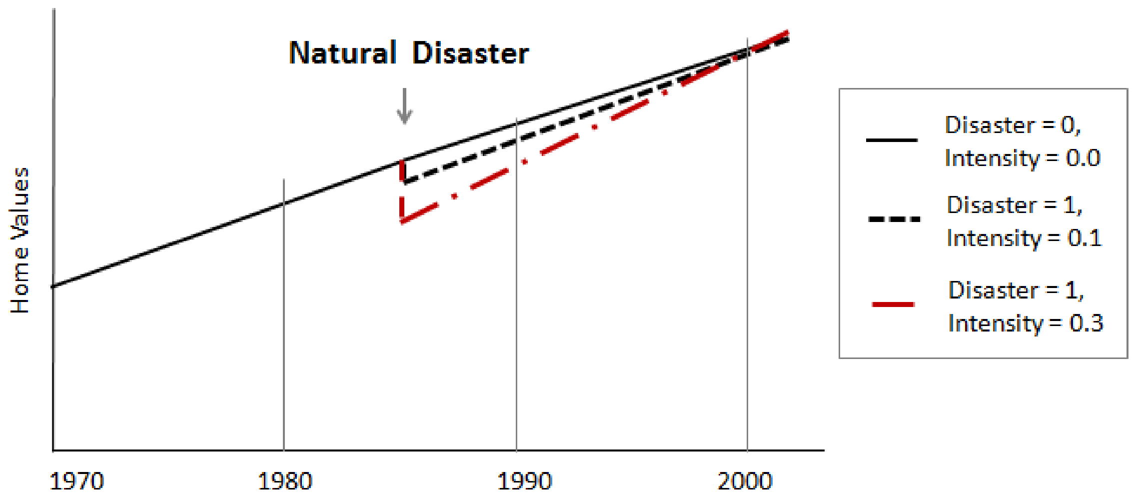


Figure 5-5. The Differential Effects of Natural Disasters on Neighborhood Home Values According to the Intensity of the Disasters

In the variance components, the statistically significant within-neighborhood variance component (σ_ε^2) for Model H_6 (0.4808) changes: The component declines by 0.25% from Model H_5 (0.4820). The between-neighborhood variance components ((σ_0^2 and σ_1^2) for Model H_6 are almost identical to those of Model H_5, suggesting the continued presence of potentially explicable residual variation in both the initial status and the rate of change. The variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is 0.0362 and statistically significant at a 99% confidence level, showing that variation in discontinuity in the elevation for DISASTER still remains. The variance component in discontinuity in the rate of change for POSTTIME between neighborhoods, σ_3^2, is very small and not statistically significant at a 90% confidence level. As a result, variability in the rate of change in home values between neighborhoods after a disaster cannot be determined.

5.4.1.2. The Differential Effects of Disasters on Neighborhood Poverty Rates According to the Intensity of the Disasters

Model P_6 in Table 5-15 includes INTENSITY in Model P_5, which explores discontinuity in the elevation and the slope of the neighborhood poverty rate trajectory after a major disaster. In the model, INTENSITY examines the difference in the change in the initial status of the poverty rates of neighborhood according to the intensity of a natural disaster. To investigate the difference in change in the slope, we do not include POSTTIME*INTENSITY because the variance component in discontinuity in the elevation for DISASTER between neighborhoods, σ_2^2, in Model P_5 is zero.

The results of Model P_6 follow: (1) The estimated initial POVERTY (poverty rates) for the average neighborhoods without the experience of major natural disasters is 0.3809 (p < .001); (2) the estimated differential in initial POVERTY between neighborhoods with and without disaster experience is 0.0262 (p < .001); (3) the estimated differential in initial POVERTY according to the intensity of the disaster is 0.0487 (p < .001); (4) the estimated rate of change in POVERTY for the average neighborhoods without experience of a major natural disaster is 0.0023 (p < .001); and (5) the estimated differential in the rate of change in POVETY between neighborhoods with and without a disaster experience is -0.0014 (p < .001). The model suggests that neighborhoods with the experience of natural disasters undergo an instant increase in their poverty rates compared to neighborhoods without the experience; on the other hand, they undergo an annual decrease in poverty rates. In addition, neighborhoods stuck by more intense disasters experience a more rapid increase in poverty rates than those struck by less intense disasters.

Table 5-15. The Differential Effects of Natural Disasters on Neighborhood Poverty Rates According to the Intensity of the Natural Disasters

	Poverty Rates	MODEL P_5		MODEL P_6	
Fixed Effects					
Initial Status	Intercept, γ_{000}	0.3811***	(0.0173)	0.3809***	(0.0173)
	INCOME, γ_{001}	-3.24E-6***	(0)	-3.18E-6***	(0)
	NEWHOME, γ_{002}	-0.0214***	(0.0031)	-0.0208***	(0.0031)
	OLDHOME, γ_{003}	0.0613***	(0.0019)	0.0623***	(0.0019)
	WHITE, γ_{004}	-0.2071***	(0.0019)	-0.2068***	(0.0019)
	HISPANIC, γ_{005}	0.1882***	(0.0036)	0.1872***	(0.0036)
	M_POP, γ_{006}	-736E-12***	(0)	-789E-12***	(0)
	M_INC, γ_{007}	-1.66E-6***	(0)	-1.63E-6***	(0)
	M_UEMP, γ_{008}	0.0015	(0.0036)	0.0019	(0.0036)
	R_POP, γ_{009}	-0.2799***	(0.0766)	-0.3238***	(0.0764)
	NATURAL, γ_{010}	0.0002	(0.0006)	0.0001	(0.0006)
	CBD, γ_{011}	0.0093***	(0.0014)	0.0097***	(0.0014)
	HIGHWAY, γ_{012}	-0.0003**	(0.0001)	-0.0003**	(0.0001)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}	**0.0316*****	(0.0031)	**0.0262*****	(0.0031)
	DISASTER* INTENS, γ_{014}			**0.0487*****	(0.0143)
Rate of Change	TIME, γ_{100}	0.0024***	(0.0002)	0.0023***	(0.0002)
	TIME*INCOME, γ_{110}	6.82E-8***	(0)	6.65E-8***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}	**-0.0017*****	(0.0002)	**-0.0014*****	(0.0002)
	POSTTIME*INTENS, γ_{130}			-	-
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.0046***	(0.0001)	0.0045***	(0.0001)
Level2	In initial status, σ_0^2	0.0004***	(0.0001)	0.0004***	(0.0001)
	In rate of change, σ_1^2	2.01E-6***	(0)	2.00E-6***	(0)
	In DISASTER, σ_2^2	**0.000197****	(0)	0.00016*	(0.0001)
	In POSTTIME, σ_3^2	**0*****	(0)	0***	(0)
Goodness-of-Fit					
	Deviance	-85774.9		-86083.5	
	AIC	-85638.9		-85945.5	
	BIC	-85246.9		-85547.8	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.5. Model Output for MODLE P_6 on Appendix)

~ p<.10; * p<.05; **p<.01; ***p<.001

Figure 5-7 illustrates the results of Model P_6, the differential effects of major hurricanes in the 1980s on neighborhood poverty rates according to the intensity of the hurricanes. The estimated poverty rates of average neighborhoods in 1970 and 1980 are 0.193 and 0.183, respectively. Regardless of their intensity, natural disasters are likely to cause an instant increase in poverty rates by 0.026. Thus, if the average neighborhoods were hit by a major hurricane in 1985, the poverty rates increased from 0.171 to 0.197. If the intensity of the hurricane was 0.5, the poverty rates increased by 0.051. However, the rate of change of the poverty rates after the disaster tended to decrease as time passed. Fifteen years after the disaster, the gap between the poverty rates of neighborhoods that experienced disaster of 0.5 intensity and those of neighborhoods that did not experience a disaster decreased by about 0.030.

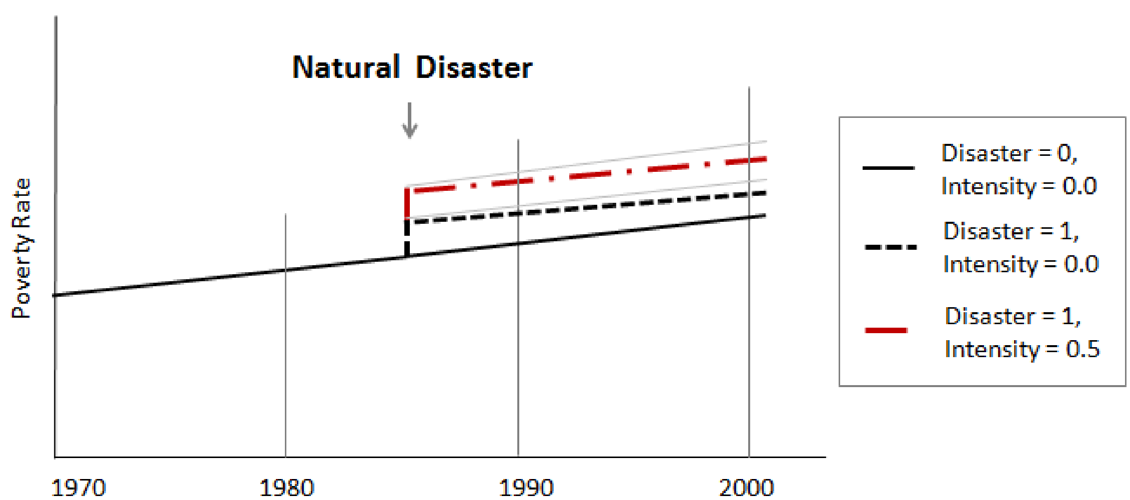


Figure 5-7. The Differential Effects of Natural Disasters on Neighborhood Poverty Rates Accoring to the Intensity of the Natural Disasters

The statistically significant within-neighborhood variance component (σ_ε^2) for Model P_6 (0.0045) is almost identical to that of Model P_5, suggesting that INTENSITY may not explain the variation in poverty rates within neighborhoods. The between-neighborhoods variance components ((σ_0^2 and σ_1^2) for Model P_6 also do not change, suggesting that the presence of potentially explicable residual variation in both the initial status and the rate of change continues. The variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is 0.0016 and statistically significant at a 95% confidence level. It declines by 18.8% from Model P_5. From the results, we can understand that INTENSITY effectively explains the differential effect of DISASTER on the change in the initial status of the poverty rates trajectory among neighborhoods.

5.4.1.3. The Differential Effects of Disasters on Neighborhood Racial Diversity According to the Intensity of the Natural Disasters

Model D_6 of Table 5-16 includes INTENSITY as a predictor of the initial status of neighborhood racial diversity trajectory in Model D_5. INTENSITY presents the differential effects of disasters on change in racial diversity according the magnitude of the disasters. In the model, most of variables that may affect the initial status of home values are significant with the expected signs. The main results of the analysis for Model D_6 can be summarized in three ways: (1) The estimated initial DIVERSITY for the average neighborhoods without experience of major natural disasters is 0.5674 ($p < 0.001$); (2) the estimated differential in initial DIVERSITY between neighborhoods with and without disaster experience is -0.0132 ($p < 0.01$); and (3) the estimated differential in

Table 5-16. The Differential Effects of Natural Disasters on Neighborhood Racial Diversity According to the Intensity of the Natural Disasters

Diversity		MODEL D_5		MODEL D_6	
Fixed Effects					
Initial Status	Intercept, γ_{000}	0.5656***	(0.0438)	0.5674***	(0.0438)
	INCOME, γ_{001}	-7.74E-7***	(0)	-7.57E-7***	(0)
	NEWHOME, γ_{002}	0.0168**	(0.0071)	0.0159*	(0.0071)
	OLDHOME, γ_{003}	0.0130**	(0.0044)	0.0115**	(0.0044)
	WHITE, γ_{004}	-0.3496***	(0.0044)	-0.3507***	(0.0044)
	HISPANIC, γ_{005}	0.6484***	(0.0083)	0.6526***	(0.0084)
	M_POP, γ_{006}	-1.31E-9***	(0)	-1.44E-9***	(0)
	M_INC, γ_{007}	-4.26E-7***	(0)	-3.92E-7***	(0)
	M_UEMP, γ_{008}	-0.0606***	(0.0087)	-0.0611***	(0.0087)
	R_POP, γ_{009}	-0.0858	(0.1829)	-0.0865	(0.1830)
	NATURAL, γ_{010}	-0.0103***	(0.0015)	-0.0103***	(0.0015)
	CBD, γ_{011}	-0.0297***	(0.0037)	-0.0296***	(0.0037)
	HIGHWAY, γ_{012}	-0.0019***	(0.0003)	-0.0020***	(0.0003)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}	**-0.0095**	(0.0065)	**-0.0132***	(0.0065)
	DISASTER* INTENS, γ_{014}			**0.2099***	(0.0951)
Rate of Change	TIME, γ_{100}	0.0079***	(0.0005)	0.0078***	(0.0005)
	TIME*INCOME, γ_{110}	2.27E-9***	(0)	-1.84E-9***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}	**-0.00047**	(0.0005)	**-0.0002**	(0.0006)
	POSTTIME*INTENS, γ_{130}			**-0.0165**	(0.0107)
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.0233***	(0.0002)	0.0232***	(0.0002)
Level2	In initial status, σ_0^2	0.0055***	(0.0004)	0.0055***	(0.0004)
	In rate of change, σ_1^2	5.445E-6***	(0)	5.537E-6***	(0)
	In DISASTER, σ_2^2	0.00029	(0.0003)	0.00007	(0.0003)
	In POSTTIME, σ_3^2	3.061E-6~	(2.04E-6)	4.119E-6*	(2.159E-6)
Goodness-of-Fit					
	Deviance	-28946.1		-28995.4	
	AIC	-28808.1		-28853.4	
	BIC	-28410.3		-28442.2	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.6. Model Output for MODLE D_6 on Appendix)

~ p<.10; * p<.05; **p<.01; ***p<.001

initial DIVERSITY according to the intensity of the disaster is 0.2099 ($p < 0.01$); (4) the estimated rate of change in DIVERSITY for the average neighborhoods without an experience of a major natural disaster is 0.0078 ($p < 0.001$); (5) the estimated differential in the rate of change in DIVERSITY between neighborhoods with a disaster experience and the others is -0.0002 (but it is not statistically significant at the conventional confidence level); and (6) of neighborhoods with a major disaster experience, the estimated differential in the rate of change in DIVERSITY according to its intensity is -0.0165 (which is not statistically significant).

The results show that while neighborhoods with the experience of natural disasters suffer from an instant decline in their racial diversity compared to neighborhoods without the experience, neighborhoods struck more severe disasters hit experience at larger increase in racial diversity than those struck by the less severe disasters. The effects are not likely to change according to time.

Figure 5-8 illustrates the results of Model D_6, the differential effects of major hurricanes in the 1980s on neighborhood racial diversity according to the intensity of the hurricanes. The estimated racial diversity of average neighborhoods in 1970 and 1980 are 0.259 and 0.322, respectively. Regardless of their intensity, natural disasters are likely to cause an instant decrease in poverty rates by 0.013. Thus, if the average neighborhoods were hit by a major hurricane in 1985, the racial diversity immediately decreased from 0.361 to 0.347. However, the more severe the natural disasters are, the more rapidly the racial diversity of the neighborhoods increases. If the intensity of a natural disaster is less than 0.063, racial diversity may increase. For example, a natural disaster with an intensity of 0.5 may instantly increase diversity might instantly increase diversity by 0.092. Thus, the gap between the racial diversity of neighborhoods without a disaster experience may not change over time.

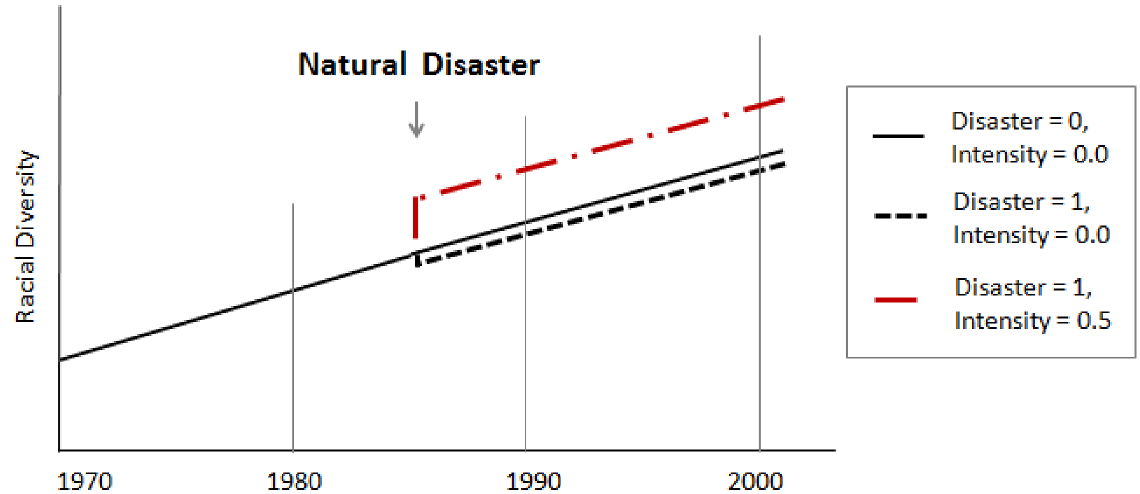


Figure 5-8. The Differential Effects of Natural Disasters on Neighborhood Racial Diversity According to thee Intensity of the Natural Disasters

The statistically significant within-neighborhood variance component (σ_ε^2) for Model D_6 (0.0232) is almost identical to that of Model D_5, suggesting that INTENSITY might not explain the variation in racial diversity within neighborhoods. The between-neighborhood variance components ((σ_0^2 and σ_1^2) for Model D_6 also do not change, suggesting that the presence of potentially explicable residual variation both in the initial status and in the rate of change continues. The variance component in discontinuity in elevation for DISASTER between neighborhoods (σ_2^2) is 0.00007, but it is not statistically significant at the conventional confidence level. We can understand that the variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is zero. The variance component in discontinuity in the rate of change for POSTTIME between neighborhoods (σ_3^2) is very small, but it is larger than that for Model D_5. From the results, we cannot determine that INTENSITY effectively explains the differential effect of disaster on changes in the slope of the racial diversity trajectory among neighborhoods.

5.4.2. Neighborhood Average Income

In this section, the analyses for the differential effects of natural disasters on neighborhood change according to neighborhood socioeconomic characteristics, particularly income, are conducted.

5.4.2.1. The Differential Effects of Disasters on Neighborhood Home Values According to Income

Model H_7 of Table 5-17 adds DISASTER*LOWINC and DISASTER*HIINC, POSTTIME*LOWINC and POSTTTIME*HIGHINC as predictors of the initial statuses and slopes, respectively, of the neighborhoods home value trajectory in Model H_5. These four predictors, which represent low-income and high-income neighborhoods with natural disaster experience in the 1980s, help us to understand the differential effects of disasters on changes in home values according to neighborhood income.

Interpretation of six fixed effects follows: (1) The estimated initial HOMEVALUE for the average neighborhoods without experience of major natural disasters is 8.0621 ($p < 0.001$); (2) the estimated differential in initial HOMEVALUE between moderate-income neighborhoods with and without disaster experience is -0.0178 (but it is not statistically significant at the conventional confidence level); (3) of neighborhoods with natural disaster experience, the estimated differentials in initial HOMEVALUE of low- and high-income neighborhoods compared to moderate-income neighborhoods are -0.0170 (not statistically significant) and -0.3508 ($p < 0.001$), respectively;

Table 5-17. The Differential Effects of Natural Disasters on Neighborhoods' Home Values According to the Neighborhood Income

Home Values		MODEL H_5		MODEL H_7	
Fixed Effects					
Initial Status	Intercept, γ_{000}	8.0903***	(0.1907)	8.0621***	(0.1912)
	INCOME, γ_{001}	0.00005***	(0)	0.00005***	(0)
	NEWHOME, γ_{002}	-0.0952**	(0.0329)	-0.0965**	(0.0330)
	OLDHOME, γ_{003}	-0.2807***	(0.0208)	-0.2790***	(0.0209)
	WHITE, γ_{004}	0.3173***	(0.0209)	0.3089***	(0.0211)
	HISPANIC, γ_{005}	-0.5645***	(0.0397)	-0.5291***	(0.0397)
	M_POP, γ_{006}	1.06E-8***	(0)	9.05E-9***	(0)
	M_INC, γ_{007}	8.60E-6***	(1.3E-6)	0.00001***	(1.4E-6)
	M_UEMP, γ_{008}	-0.0629	(0.0386)	-0.0436	(0.0382)
	R_POP, γ_{009}	19.6261***	(0.8590)	19.240***	(0.8595)
	NATURAL, γ_{010}	0.0260***	(0.0065)	0.0263***	(0.0064)
	CBD, γ_{011}	-0.1532***	(0.0162)	-0.1468***	(0.0161)
	HIGHWAY, γ_{012}	0.0015	(0.0013)	0.0013	(0.0013)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}	**-0.0766***	(0.0335)	**-0.0178**	(0.0373)
	DISASTER* LOWINC, γ_{015}			**-0.0170**	(0.0536)
	DISASTER* HIGHINC, γ_{016}			**-0.3508*****	(0.0544)
Rate of Change	TIME, γ_{100}	0.0490***	(0.0020)	0.0471***	(0.0020)
	TIME*INCOME, γ_{110}	-1.32E-6***	(0)	-1.3E-6***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}	**0.0026**	(0.0024)	**0.0010**	(0.0029)
	POSTTIME* LOWINC, γ_{140}			**-0.0132****	(0.0047)
	POSTTIME* HIGHINC, γ_{150}			**0.0277*****	(0.0048)
Variance Components					
Level1	Within-neighborhood, σ^2_e	0.4820***	(0.0040)	0.4778***	(0.0040)
Level2	In initial status, σ^2_0	0.0998***	(0.0059)	0.0944***	(0.0061)
	In rate of change, σ^2_1	0.00006***	(6.44E-6)	0.00006***	(6.3E-6)
	In DISASTER, σ^2_2	0.0354***	(0.0084)	0.0318***	(0.0082)
	In POSTTIME, σ^2_3	0.00001	(0.00003)	0.00003	(0.00003)
Goodness-of-Fit					
	Deviance	71849.3		70624.9	
	AIC	71987.3		70770.9	
	BIC	72385.0		71191.6	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.7. Model Output for MODLE H_7 on Appendix)

~ p<.10; * p<.05; **p<.01; ***p<.001

(4) the estimated rate of change in HOMEVALUE for the average neighborhoods without experience of a major natural disaster is 0.0471 ($p < 0.001$); (5) the estimated differential in the rate of change in HOMEVALUE between moderate-income neighborhoods with and without disaster experience is 0.0010 (not statistically significant); and (6) of neighborhoods with disaster experience, the estimated differential in the rate of change in HOMEVALUE of low- and high-income neighborhoods compared to moderate-income neighborhoods are -0.0132 ($p < 0.01$) and 0.0277 ($p < 0.001$), respectively.

Natural disasters appear have a negative impact on the initial status of the high-income neighborhood home value trajectory, but they might not have any impact on the initial status of low- and moderate-income neighborhood home values trajectory. However, disasters appear to have a positive effect on high-income neighborhoods, and they may not have any effect on moderate-income neighborhoods, and they seem to have a negative impact on the slope of the home values trajectory for low-income neighborhoods. While high-income neighborhoods experience an immediately decrease (-35.1%) in their home values in the aftermath of natural disasters, low- and moderate-income neighborhoods do not experience any immediate change. A natural disaster is not likely to affect an annual rate of change in home values for moderate-income neighborhoods, but it is for both low- and high-income neighborhoods; home values of low-income neighborhoods annually decrease by -1.3% after a disaster, while those of high-income neighborhoods annually increase by 2.8%. Thus, high-income neighborhoods with disaster experience recovered most of their home values by 2000 (15 years after the disaster). However, after about the same years (12.7 years), the home values of low-income neighborhoods with disaster experience ($29,365) decrease by

12.4% compared to those of low-income neighborhoods without disaster experience ($33,509). As a result, the gap between the home values of low-income neighborhoods that experienced a natural disaster and those of other neighborhoods appeared to increase over time. Figure 5-9 illustrates the differential effects of major hurricanes in the 1980s on neighborhood home values according to neighborhood income.

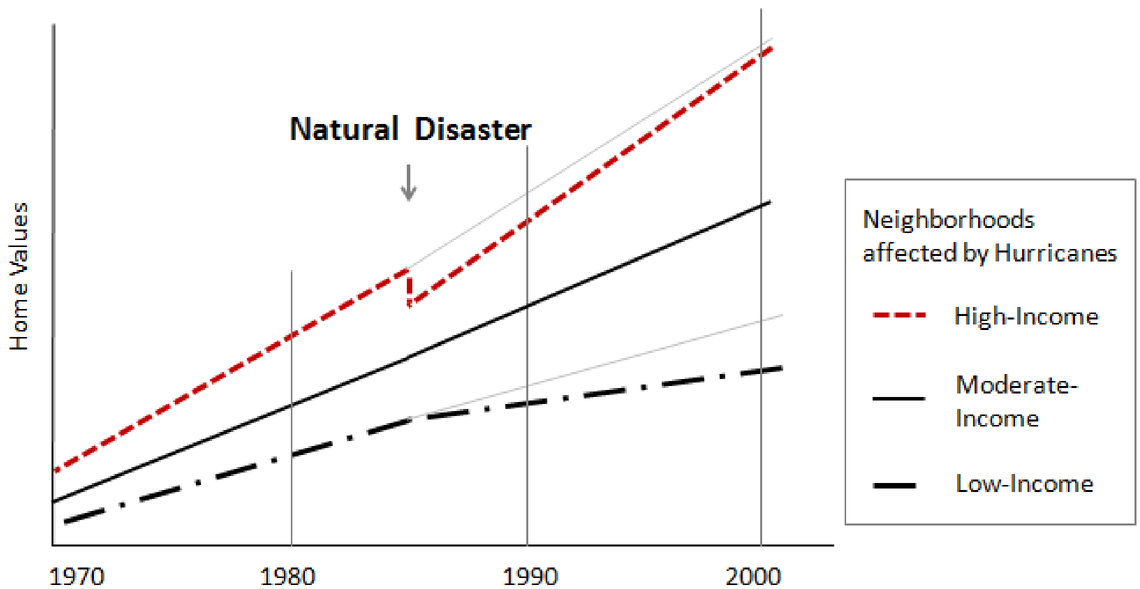


Figure 5-9. The Differential Effects of Natural Disasters on Neighborhood Home Values According to the Neighborhood Income

The statistically significant within-neighborhood variance component (σ_ε^2) for Model H_7 (0.4778) does not significantly change compared to that for Model H_5, suggesting that DISASTER*LOWINC, DISASTER*HIGHINC, POSTTIME*LOWINC and POSTTIME*HIGHINC may not significantly be related to the variation in home values within neighborhoods. The between-neighborhood variance components (σ_0^2 and σ_1^2) for Model H_7 are slightly smaller than that of Model H_5, indicating that these four disaster variables may explain the variation in home values between neighborhoods and that the continued presence of potentially explicable residual variation both in the initial status and in the rate of change. The variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is 0.0318 and statistically significant at a 99.9% confidence level, but it declines by 10.2% from Model H_5. While the variation in discontinuity in the elevation for DISASTER still remains, it decreases when DISASTER*LOWINC and DISASTER*HIGHINC are added. Thus, we determine that DISASTER*LOWINC and DISASTER*HIGHINC effectively explain the differential effect of DISASTER on the change in the initial status of the home value trajectory among neighborhoods.

5.4.2.2. The Differential Effects of Disasters on Neighborhood Poverty Rates According to the Neighborhood Income

Model P_7 in Table 5-18 includes DISASTER*LOWINC and DISASTER* HIGHINC in Model P_5, which explores the discontinuity in the elevation and the slope of neighborhoods poverty rates trajectory, interrupted by a major disaster. In the model, DISASTER*LOWINC and DISASTER*HIGHINC show the differences in the change in the initial status of neighborhoods' poverty rates according to neighborhood income. The model does not include POSTTIME*LOWINC and POSTTIME*HIGHINC in the investigation of the difference in the change in the slope because the variance component in discontinuity in the elevation for DISASTER between neighborhoods, σ_2^2, in Model P_5 is zero ($p < 0.001$).

Table 5-18. The Differential Effects of Natural Disasters on Neighborhood Poverty Rates According to the Neighborhood Income

Poverty Rates		MODEL P_5		MODEL P_7	
Fixed Effects					
Initial Status	Intercept, γ_{000}	0.3811***	(0.0173)	0.3768***	(0.0176)
	INCOME, γ_{001}	-3.24E-6***	(0)	-3.35E-6***	(0)
	NEWHOME, γ_{002}	-0.0214***	(0.0031)	-0.0222***	(0.0031)
	OLDHOME, γ_{003}	0.0613***	(0.0019)	0.0620***	(0.0019)
	WHITE, γ_{004}	-0.2071***	(0.0019)	-0.2005***	(0.0019)
	HISPANIC, γ_{005}	0.1882***	(0.0036)	0.1780***	(0.0036)
	M_POP, γ_{006}	-736E-12***	(0)	-644E-12***	(0)
	M_INC, γ_{007}	-1.66E-6***	(0)	-1.63E-6***	(0)
	M_UEMP, γ_{008}	0.0015	(0.0036)	0.0007	(0.0036)
	R_POP, γ_{009}	-0.2799***	(0.0766)	-0.2578***	(0.0766)
	NATURAL, γ_{010}	0.0002	(0.0006)	0.0001	(0.0006)
	CBD, γ_{011}	0.0093***	(0.0014)	0.0092***	(0.0014)
	HIGHWAY, γ_{012}	-0.0003**	(0.0001)	-0.0003**	(0.0001)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}	**0.0316*****	(0.0031)	**0.0116*****	(0.0033)
	DISASTER* LOWINC, γ_{015}			**0.0615*****	(0.0025)
	DISASTER* HIGHINC, γ_{016}			**0.0476*****	(0.0026)
Rate of Change	TIME, γ_{100}	0.0024***	(0.0002)	0.0024***	(0.0002)
	TIME*INCOME, γ_{110}	6.82E-8***	(0)	6.96E-8***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}	**-0.0017*****	(0.0002)	**-0.0020*****	(0.0002)
	POSTTIME* LOWINC, γ_{140}			-	-
	POSTTIME* HIGHINC, γ_{150}			-	-
Variance Components					
Level1	Within-neighborhood, σ_ε^2	0.0046***	(0.0001)	0.0045***	(0.00004)
Level2	In initial status, σ_0^2	0.0004***	(0.0001)	0.0004***	(0.0001)
	In rate of change, σ_1^2	2.01E-6***	(0)	1.94E-6***	(0)
	In DISASTER, σ_2^2	**0.000197****	(0)	**0.00013***	(0.0001)
	In POSTTIME, σ_3^2	**0*****	(0)	0***	(0)
Goodness-of-Fit					
	Deviance	-85774.9		-85951.9	
	AIC	-85638.9		-85813.9	
	BIC	-85246.9		-85416.2	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.8. Model Output for MODLE P_7 on Appendix)

~ p<.10; * p<.05; **p<.01; ***p<.001

The results of Model P_7 follow: (1) The estimated initial POVERTY for the average neighborhoods without experience of major natural disasters is 0.3768 ($p < 0.001$); (2) the estimated differential in initial POVERTY between moderate-income neighborhoods with and without disaster experience is 0.0116 ($p < 0.001$); (3) of neighborhoods with a natural disaster experience, the estimated differentials in initial POVERTY of low- and high-income neighborhoods compared to moderate-income neighborhoods are 0.0615($p < 0.001$) and 0.0476 ($p < 0.001$), respectively; (4) the estimated rate of change in POVERTY for the average neighborhoods without experience of major natural disasters is 0.0024 ($p < .001$); and (5) the estimated differential in the rate of change in POVERTY between neighborhoods with and without disaster experience is -0.0020 ($p < 0.001$).

According to the results, natural disasters are likely to have a positive impact on the initial status of the neighborhood poverty rate trajectory in all neighborhoods regardless of their income. Figure 5-10 illustrates the differential effects of major hurricanes in the 1980s on neighborhood's poverty rates according to neighborhood income. While low-income neighborhoods (0.0731) immediately suffer from the large increase in poverty rates after natural disasters, moderate-income neighborhoods (0.0116) experience the smallest increase. On the other hand, natural disasters are likely to have a negative impact on the rates of change in the trajectory, suggesting that the poverty rates of neighborhoods annually decrease after a natural disaster. Fifteen years after the disaster, the poverty rates of moderate-income neighborhoods with a disaster experience appear to be only slightly lower than those of same income neighborhoods without a disaster experience in 2000; however, the poverty rates of high- and low-income neighborhoods that have experienced a disaster are still higher than those of same-income neighborhoods that have not.. In particular, the gap between the poverty rates of neighborhoods with and without disaster experience appears to be the largest for low-income neighborhoods, but it appears to decrease over time.

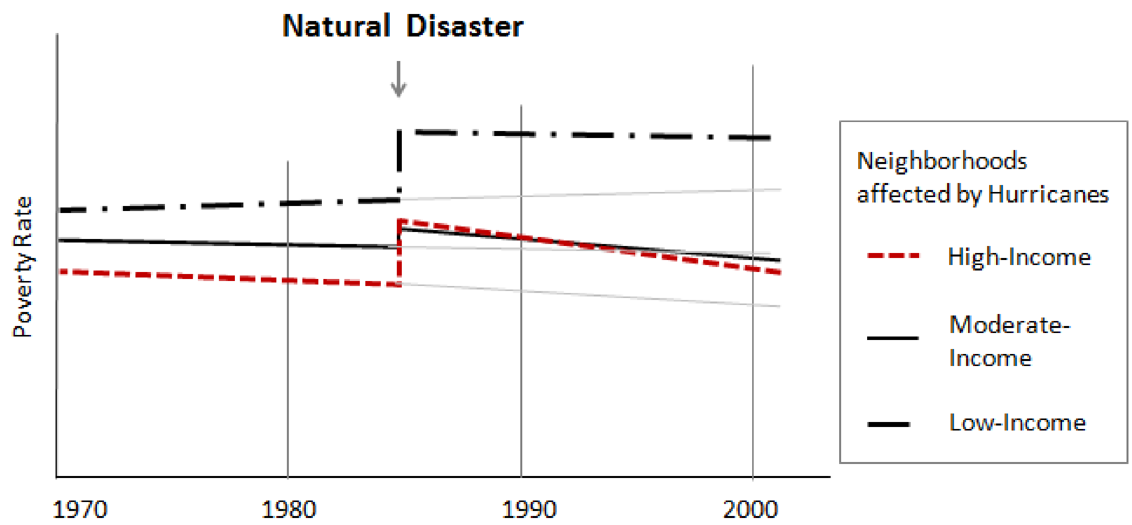


Figure 5-10. The Differential Effects of Natural Disasters on Neighborhood Poverty Rates According to the Neighborhood Income

The statistically significant within-neighborhood variance component (σ_ε^2) for Model P_7 (0.0044) is almost identical to that of Model P_5 (0.0046), suggesting that DISASTER*LOWINC and DISASTER*HIGHINC may not be related to the variation in poverty rates within neighborhoods. The between-neighborhood variance components (σ_0^2 and σ_1^2) for Model P_7 also do not change, suggesting that the presence of potentially explicable residual variation in both the initial status and the rate of change continues. The variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is 0.00013 and statistically significant at a 95% confidence level and declines by 34.0% from Model C_P1. The results show that DISASTER*LOWINC and DISASTER*HIGHINC effectively explain the differential effect of DISASTER on the change in the initial status of the poverty rate trajectory among neighborhoods.

5.4.2.3. The Differential Effects of Disasters on Neighborhood Racial Diversity According to the Neighborhood Income

In Model D_7 of Table 5-19, DISASTER*LOWINC, DISASTER*HIGHINC, POSTTIME*LOWINC, and POSTTIME*HIGHINC present the differential effects of disasters on changes in racial diversity according to neighborhood income. The main results of the analysis for Model D_7 can be summarized in six ways: (1) The estimated initial DIVERSITY for the average neighborhoods without experience of a major natural disaster is 0.5736 (p < 0.001); (2) the estimated differential in initial DIVERSITY between moderate-income neighborhoods with and without disaster experience is 0.0023 (but it is not statistically significant at a conventional confidence level); and (3) of neighborhoods with natural disaster experience, the estimated differentials in initial DIVERSITY of low- and high-income neighborhoods compared to moderate-income neighborhoods are -0.0281 (p < 0.05) and -0.0421 (p < 0.001), respectively; (4)) the estimated rate of change in DIVERSITY for the average neighborhoods without experience of a major natural disaster is 0.0076 (p < 0.001); (5) the estimated differential in the rate of change in DIVERSITY between moderate-income neighborhoods with and without disaster experience is -0.0006 (not statistically significant); and (6) of neighborhoods with disaster experience, the estimated differentials in the rate of change

Table 5-19. The Differential Effects of Natural Disasters on Neighborhood Racial Diversity According to the Neighborhood Income

Diversity		MODEL D_5		MODEL D_7	
Fixed Effects					
Initial Status	Intercept, γ_{000}	0.5656***	(0.0438)	0.5736***	(0.0448)
	INCOME, γ_{001}	-7.74E-7***	(0)	-6.9E-7***	(0)
	NEWHOME, γ_{002}	0.0168**	(0.0071)	0.0184**	(0.0071)
	OLDHOME, γ_{003}	0.0130**	(0.0044)	0.0111**	(0.0044)
	WHITE, γ_{004}	-0.3496***	(0.0044)	-0.3520***	(0.0045)
	HISPANIC, γ_{005}	0.6484***	(0.0083)	0.6576***	(0.0084)
	M_POP, γ_{006}	-1.31E-9***	(0)	-1.4E-9***	(0)
	M_INC, γ_{007}	-4.26E-7***	(0)	-2.2E-7***	(0)
	M_UEMP, γ_{008}	-0.0606***	(0.0087)	-0.0609***	(0.0088)
	R_POP, γ_{009}	-0.0858	(0.1829)	-0.0816	(0.1852)
	NATURAL, γ_{010}	-0.0103***	(0.0015)	-0.0105***	(0.0015)
	CBD, γ_{011}	-0.0297***	(0.0037)	-0.0304***	(0.0037)
	HIGHWAY, γ_{012}	-0.0019***	(0.0003)	-0.0020***	(0.0003)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}	**-0.0095**	(0.0065)	**0.0023**	(0.0075)
	DISASTER* LOWINC, γ_{015}			**-0.0281***	(0.0113)
	DISASTER* HIGHINC, γ_{016}			**-0.0421*****	(0.0119)
Rate of Change	TIME, γ_{100}	0.0079***	(0.0005)	0.0076***	(0.0005)
	TIME*INCOME, γ_{110}	2.27E-9***	(0)	-3.1E-9***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}	**-0.00047**	(0.0005)	**-0.0006**	(0.0006)
	POSTTIME* LOWINC, γ_{140}			**-0.0012**	(0.0010)
	POSTTIME* HIGHINC, γ_{150}			**0.0032****	(0.0011)
Variance Components					
Level1	Within-neighborhood, σ_{ε}^2	0.0233***	(0.0002)	0.0233***	(0.0002)
Level2	In initial status, σ_0^2	0.0055***	(0.0004)	0.0056***	(0.0004)
	In rate of change, σ_1^2	5.45E-6***	(0)	5.3E-6***	(0)
	In DISASTER, σ_2^2	0.00029	(0.0003)	0.0002	(0.0003)
	In POSTTIME, σ_3^2	3.061E-6~	(2.04E-6)	2.8E-6~	(1.97E-6)
Goodness-of-Fit					
	Deviance	-28946.1		-28571.6	
	AIC	-28808.1		-28425.6	
	BIC	-28410.3		-28005.0	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.9. Model Output for MODLE D_7 on Appendix)

~ p<.10; * p<.05; **p<.01; ***p<.001

DIVERSITY of low- and high-income neighborhoods compared to moderate-income neighborhoods are -0.0012 (not statistically significant) and 0.0032 ($p < 0.05$), respectively.

The results show that natural disasters may have a negative impact on the initial status of low- and high-income neighborhood racial diversity trajectory; but not impact on the initial status of the moderate-income neighborhood racial diversity trajectory. However, while the disasters appear to have a positive impact on the slope of the home value trajectory for high- income neighborhoods, they do not appear to have the same effect on that for low- and moderate-income neighborhoods.

Figure 5-11 illustrates the differential impact of natural disasters on neighborhood racial diversity according to income. In the aftermath of a natural disaster, low- and high-income neighborhoods experience the immediately decrease by -0.028 and -0.042, respectively, in racial diversity, while moderate-income neighborhoods do not appear to undergo such a change. The racial diversity of low- and moderate-income neighborhoods with disaster experience is likely to change annually the same rate as those without disaster experience while those of high-income neighborhoods with disaster experience increase annually by 0.0032. Low-income neighborhoods whose residents are relatively racially diverse appear to experience a rapid decline in their diversity after a natural disaster. As a result, the racial diversity of low-income neighborhoods with disaster experience tends to be lower than that of moderate-income neighborhoods. Although high-income neighborhoods show a sharp decrease in their racial diversity after a natural disaster, they appear to recover rapidly in this respect.

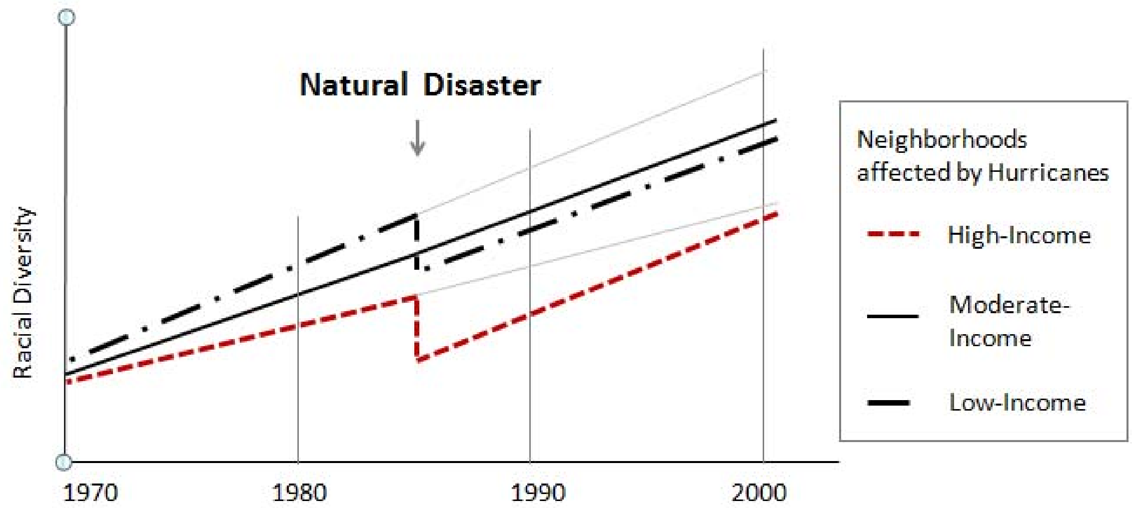


Figure 5-11. The Differential Effects of Natural Disasters on Neighborhood Racial Diversity According to the Neighborhood Income

The statistically significant within-neighborhood variance component (σ_ε^2) for Model D_7 (0.0233) is identical to that of Model D_5, suggesting that DISASTER* LOWINC, DISASTER*HIGHINC, POSTTIME*LOWINC and POSTTIME*HIGHINC may not be linked with the variation in racial diversity within neighborhoods. The between-neighborhood variance components (σ_0^2 and σ_1^2) for Model D_7 typically do not change, indicating that the presence of potentially explicable residual variation in the initial status and the rate of change continues. The variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is 0.00020, but it is not statistically significant at the conventional confidence level. Therefore, we do not reject the null hypothesis that the variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is zero. The variance component in discontinuity in the rate of change for DISASTER between neighborhoods (σ_3^2) is statistically significant at the conventional confidence level. It declines by 7.50% from Model D_5. The results show that the interaction predictor of DISASTER and INCOME effectively explains the differential effect of DISASTER on the change in both the initial status and the slope of the racial diversity trajectory among neighborhoods.

5.4.3. The Role of Municipalities

One of main hypotheses in this dissertation is that neighborhoods located in municipalities with a stronger political position are more likely to experience growth or improvement after a natural disaster. This section shows the results of the analyses for the various effects of natural disasters on neighborhood change according to the role of local municipalities which neighborhoods belong to. As discussed in the variable measures section, the role of local municipalities is measured by whether the local municipalities are central cities in metropolitan areas. Three models represent the changes in the major outcomes of neighborhood change (i.e., home values, poverty rates, and racial diversity).

5.4.3.1. The Differential Effects of Disasters on Neighborhood Home Values According to the Role of Municipality

Model H_8 in Table 5-20 includes DISASTER*CENCITY and POSTTIME* CENCITY as predictors of the initial status and the change of rate of the neighborhood home value trajectory. The interaction variables present the differential effects of disasters on change in home values according to the role of local municipalities to which neighborhoods belong. The results of the model can be summarized in several ways: (1)

Table 5-20. The Differential Effects of Natural Disasters on Neighborhood Home Values According to the Role of Municipality

Home Values		MODEL H_5		MODEL H_8	
Fixed Effects					
Initial Status	Intercept, γ_{000}	8.0903***	(0.1907)	8.0789***	(0.1913)
	INCOME, γ_{001}	0.00005***	(0)	0.00005***	(0)
	NEWHOME, γ_{002}	-0.0952**	(0.0329)	-0.0950**	(0.0329)
	OLDHOME, γ_{003}	-0.2807***	(0.0208)	-0.2801***	(0.0208)
	WHITE, γ_{004}	0.3173***	(0.0209)	0.3187***	(0.0209)
	HISPANIC, γ_{005}	-0.5645***	(0.0397)	-0.5682***	(0.0397)
	M_POP, γ_{006}	1.06E-8***	(0)	1.07E-8***	(0)
	M_INC, γ_{007}	8.60E-6***	(1.3E-6)	8.41E-6***	(1.3E-6)
	M_UEMP, γ_{008}	-0.0629	(0.0386)	-0.0541	(0.0387)
	R_POP, γ_{009}	19.6261***	(0.8590)	19.6601***	(0.8597)
	NATURAL, γ_{010}	0.0260***	(0.0065)	0.0274***	(0.0065)
	CBD, γ_{011}	-0.1532***	(0.0162)	-0.1508***	(0.0163)
	HIGHWAY, γ_{012}	0.0015	(0.0013)	0.0015	(0.0013)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}	**-0.0766****	(0.0335)	**-0.1181******	(0.0359)
	DISASTER* CENCITY, γ_{017}			**0.2821******	(0.0606)
Rate of Change	TIME, γ_{100}	0.0490***	(0.0020)	0.0493***	(0.0020)
	TIME*INCOME, γ_{110}	-1.32E-6***	(0)	-1.32E-6***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}	**0.0026**	(0.0024)	**-0.0033**	(0.0028)
	POSTTIME*CENCITY, γ_{160}			**-0.0041**	(0.0046)
Variance Components					
Level1	Within-neighborhood, σ_{ε}^2	0.4820***	(0.0040)	0.4817***	(0.0040)
Level2	In initial status, σ_0^2	0.0998***	(0.0059)	0.1008***	(0.0064)
	In rate of change, σ_1^2	0.00006***	(6.44E-6)	0.00006***	(6.6E-6)
	In DISASTER, σ_2^2	0.0354***	(0.0084)	0.0182**	(0.0073)
	In POSTTIME, σ_3^2	0.00001	(0.00003)	0.00003	(0.00004)
Goodness-of-Fit					
	Deviance	71849.3		71830.5	
	AIC	71987.3		71972.5	
	BIC	72385.0		72381.8	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.10. Model Output for MODLE H_8 on Appendix)

~ p<.10; * p<.05; **p<.01; ***p<.001

The estimated initial HOMEVALUE for the average neighborhoods without experience of a major natural disaster is 8.080 ($p < 0.001$); (2) the estimated differential in initial HOMEVALUE between neighborhoods with and without disaster experience is -0.1181 ($p < 0.001$); (3) of neighborhoods with a disaster experience, the estimated differential in initial HOMEVALUE for neighborhoods located in the central cities (CENCITY) is 0.2831 ($p < 0.001$); (4) the estimated rate of change in HOMEVALUE for the average neighborhoods without experience of a major natural disaster is 0.0493 ($p < .001$); (5) the estimated differential in the rate of change in HOMEVALUE between neighborhoods with disaster experience and the others is -0.0033 (not statistically significant); and (6) of neighborhoods with a disaster experience, the estimated differential in the rate of change in HOMEVALUE between neighborhoods in the central cities (CENCITY) and non-central city areas is -0.0041 (not statistically significant).

The results show that a natural disaster experience is likely to cause a differential change in neighborhood home values according to their role (central cities or non-central cities) (see Figure 5-12). Neighborhoods that suffer major natural disasters tend to undergo an instant decline (-11.8%) in their home values. If the neighborhoods belong to central cities, however, they are more likely to experience an instant increase (16.4%) in home values after natural disasters. The estimated home values of the average neighborhoods in 1970 and 1980 are \$7,058 and \$16,361, respectively. If the average neighborhoods were hit by a major natural disaster in 1985, their estimated home values immediately decreases by \$2,948 (\$23,513), compared to those of non-disaster neighborhoods (\$26,461). Of all the neighborhoods, however, those in the central cities experience an instant increase in their home values. These effects of natural disasters on home values tend to remain over time. As a result, in 2000, the home values of disaster neighborhoods in the central cities are typically higher than those of non-disaster neighborhoods while those of disaster-neighborhoods in non-central cities continue to be lower.

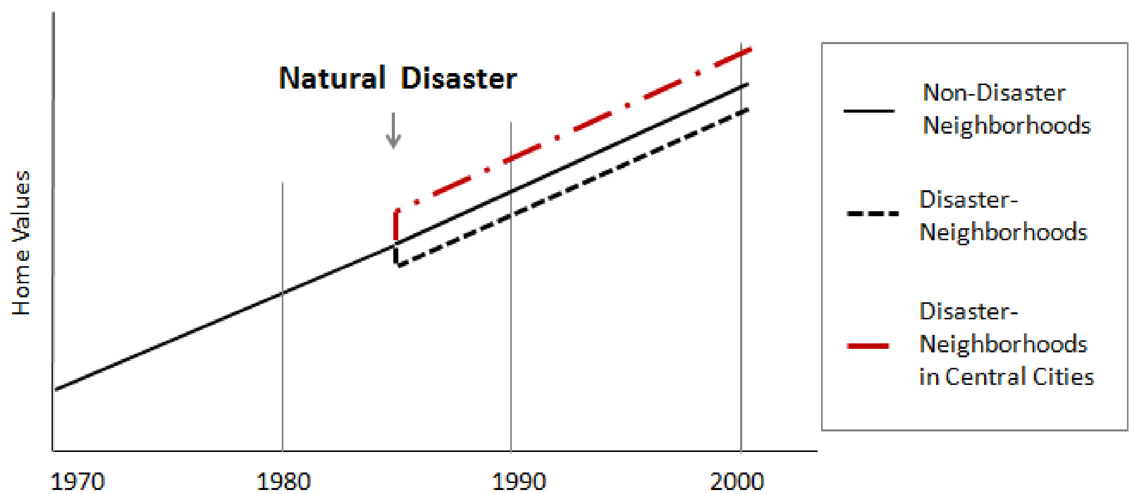


Figure 5-12. The Differential Effects of Natural Disasters on Neighborhood Home Values According to the Role of Municipality

The statistically significant within-neighborhood variance component (σ_ε^2) for Model H_8 (0.4817) only slightly changes. The between-neighborhood variance components (σ_0^2 and σ_1^2) for the model are also identical to those of Model H_5, suggesting the continued presence of potentially explicable residual variation in both the initial status and the rate of change. The variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is 0.0182 and statistically significant at a 90% confidence level. It declines by 48.6% from Model H_5, suggesting that DISASTER*CCITY effectively explains the differential effect of DISASTER on changes in the initial status of the home value trajectory among neighborhoods by reducing by about half of the variation in discontinuity in the elevation for DISASTER between neighborhoods.

5.4.3.2. The Differential Effects of Disasters on Neighborhood Poverty Rates According to the Role of Municipality

Model P_8 in Table 5-21 includes DISASTER*CCITY in Model P_5, which explores a discontinuity in the elevation and the slope of the neighborhood poverty rate trajectory by a major disaster. In the model, the interaction predictor of DISASTER and CCITY examines the difference in the change in the initial status of neighborhood poverty rates according to the role of the local municipalities in which neighborhoods reside. To investigate the difference in the change in the slope, this model includes POSTIME, but it does not include POSTTIME*CCITY because the variance component in discontinuity in the elevation for DISASTER between neighborhoods, σ_2^2, in Model C_P1 is zero.

The results of Model P_8 are as follows: (1) The estimated initial POVERTY for the average neighborhoods without experience of major natural disasters is 0.3817 ($p < .001$); (2) the estimated differential in initial POVERTY between neighborhoods with and without disaster experience is 0.0351 ($p < .001$); (3) the estimated differential in initial POVERTY according to whether or not the neighborhoods were located in the central cities is -0.0174 ($p < .01$); (4) the estimated rate of change in POVERTY for the average neighborhoods without experience of major natural disaster is 0.0023 ($p < .001$); and (5) the estimated differential in the rate of change in POVERTY between

Table 5-21. The Differential Effects of Natural Disasters on Neighborhoods' Poverty Rates According to the Role of Municipality

Poverty Rates		MODEL P_5		MODEL P_8	
Fixed Effects					
Initial Status	Intercept, γ_{000}	0.3811***	(0.0173)	0.3817***	(0.0173)
	INCOME, γ_{001}	-3.24E-6***	(0)	-3.23E-6***	(0)
	NEWHOME, γ_{002}	-0.0214***	(0.0031)	-0.0214***	(0.0031)
	OLDHOME, γ_{003}	0.0613***	(0.0019)	0.0612***	(0.0019)
	WHITE, γ_{004}	-0.2071***	(0.0019)	-0.2071***	(0.0019)
	HISPANIC, γ_{005}	0.1882***	(0.0036)	0.1885***	(0.0036)
	M_POP, γ_{006}	-736E-12***	(0)	-742E-12***	(0)
	M_INC, γ_{007}	-1.66E-6***	(0)	-1.64E-6***	(0)
	M_UEMP, γ_{008}	0.0015	(0.0036)	0.0010	(0.0036)
	R_POP, γ_{009}	-0.2799***	(0.0766)	-0.2795***	(0.0766)
	NATURAL, γ_{010}	0.0002	(0.0006)	0.0001	(0.0006)
	CBD, γ_{011}	0.0093***	(0.0014)	0.0092***	(0.0014)
	HIGHWAY, γ_{012}	-0.0003**	(0.0001)	-0.0003**	(0.0001)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}	**0.0316*****	(0.0031)	**0.0351*****	(0.0033)
	DISASTER* CENCITY, γ_{017}			**-0.0174****	(0.0050)
Rate of Change	TIME, γ_{100}	0.0024***	(0.0002)	0.0023***	(0.0002)
	TIME*INCOME, γ_{110}	6.82E-8***	(0)	6.81E-8***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}	**-0.0017*****	(0.0002)	**-0.0017*****	(0.0002)
	POSTTIME*CENCITY, γ_{160}			-	-
Variance Components					
Level1	Within-neighborhood, σ_{ε}^2	0.0046***	(0.0001)	0.0046***	(0.0001)
Level2	In initial status, σ_0^2	0.0004***	(0.0001)	0.0004***	(0.0001)
	In rate of change, σ_1^2	2.01E-6***	(0)	2.05E-6***	(0)
	In DISASTER, σ_2^2	**0.000197****	(0)	0.000085	(0.0001)
	In POSTTIME, σ_3^2	**0*****	(0)	0***	(0)
Goodness-of-Fit					
	Deviance	-85774.9		-85784.4	
	AIC	-85638.9		-85646.4	
	BIC	-85246.9		-85248.7	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.11. Model Output for MODLE P_8 on Appendix)
~ p<.10; * p<.05; **p<.01; ***p<.001

neighborhoods with and without disaster experience is -0.0017 (p < .001). These findings suggest that although neighborhoods with experience of natural disasters appear to experience an instant increase in their poverty rates compared to neighborhoods without the experience, they may experience an annual decrease in poverty rates. In addition, neighborhoods located in the non-central cities areas tended to experience more rapid increase in poverty rates than those located in the central cities.

Figure 5-13 represents the results of Model P_8, the differential effects of major hurricanes in the 1980s on neighborhood poverty rates according to the role of municipality. The estimated poverty rate of average neighborhoods in 1970 was 0.193. After the natural disasters in 1985, the elevation instantly increased by 0.035, but its rate of change annually decreased by 0.0017. Of the neighborhoods affected by a natural disaster, those in the central cities appeared to experience a less instant increase in their poverty rates (0.018) than other neighborhoods, but the annual rate of decrease was the same.

The statistically significant within-neighborhood variance component (σ_ε^2) for Model P_8 (0.0046) is the same as that of Model P_5, suggesting that DISASTER* CCITY may not be related to the variation in poverty rates within neighborhoods. The between-neighborhood variance components (σ_0^2 and σ_1^2) for P_8 also do not change, indicating that the presence of potentially explicable residual variation in both the initial status and the rate of change continues. The variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is 0.000085, but it is not statistically significant at conventional the confidence level. We cannot reject the null hypothesis that σ_2^2 is zero. Thus, we find that DISASTER*CCITY effectively explains the differential effect of DISASTER on the change in the initial status of the poverty rate trajectory among neighborhoods.

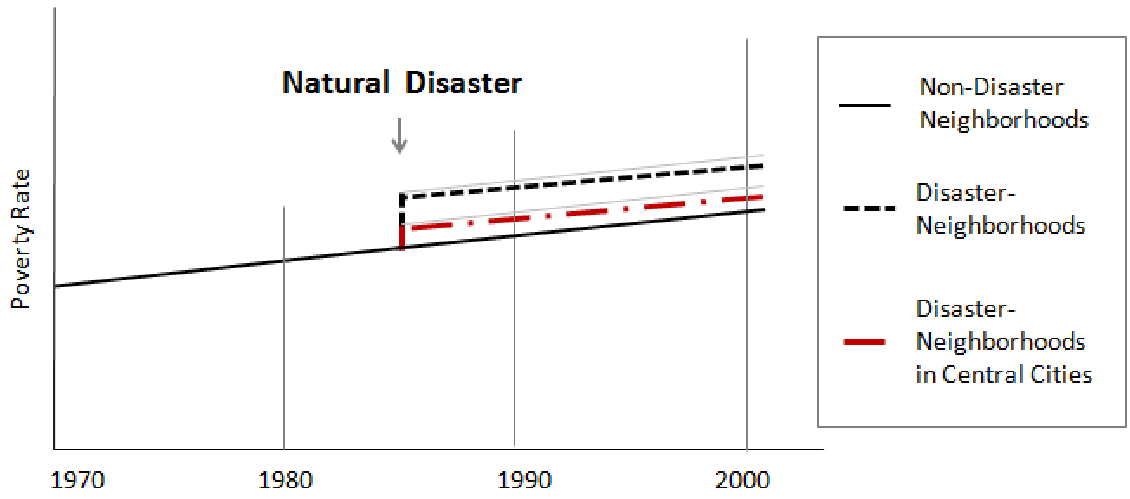


Figure 5-13. The Differential Effects of Natural Disasters on Neighborhood Poverty Rates accoring to the Role of Muncipality

5.4.3.3. The Differential Effects of Disasters on Neighborhood Racial Diversity According to Municipalities

In Model D_8 of Table 5-22, DISASTER*CENCITY and POSTTIME*CENCITY present the differential effects of disasters on the change in racial diversity according to the role of local municipalities the which the neighborhoods belong. In the model, most of the variables that may affect the initial status of home values are significant with the expected signs. The main results of the analysis for Model D_8 follows: (1) The estimated initial DIVERSITY for the average neighborhoods not experiencing a major natural disaster is 0.5660 ($p < 0.001$); (2) the estimated differential in initial DIVERSITY between neighborhoods with and without disaster experience is -0.0074 (not statistically significant at conventional confidence level); (3) the estimated differential in initial DIVERSITY according to whether or not neighborhoods belong to the central cities of

Table 5-22. The Differential Effects of Natural Disasters on Neighborhoods' Racial Diversity According to the Role of Municipality

	Diversity	MODEL D_5		MODEL D_8	
Fixed Effects					
Initial Status	Intercept, γ_{000}	0.5656***	(0.0438)	0.5660***	(0.0438)
	INCOME, γ_{001}	-7.74E-7***	(0)	-7.67E-7***	(0)
	NEWHOME, γ_{002}	0.0168**	(0.0071)	0.0169*	(0.0071)
	OLDHOME, γ_{003}	0.0130**	(0.0044)	0.0129**	(0.0044)
	WHITE, γ_{004}	-0.3496***	(0.0044)	-0.3496***	(0.0044)
	HISPANIC, γ_{005}	0.6484***	(0.0083)	0.6484***	(0.0083)
	M_POP, γ_{006}	-1.31E-9***	(0)	-1.31E-9***	(0)
	M_INC, γ_{007}	-4.26E-7***	(0)	-3.72E-7***	(0)
	M_UEMP, γ_{008}	-0.0606***	(0.0087)	-0.0611***	(0.0087)
	R_POP, γ_{009}	-0.0858	(0.1829)	-0.0830	(0.1829)
	NATURAL, γ_{010}	-0.0103***	(0.0015)	-0.0104***	(0.0015)
	CBD, γ_{011}	-0.0297***	(0.0037)	-0.0298***	(0.0037)
	HIGHWAY, γ_{012}	-0.0019***	(0.0003)	-0.0019***	(0.0003)
	Effect of Disaster on the Initial Status				
	DISASTER, γ_{013}	**-0.0095**	(0.0065)	**-0.0074**	(0.0075)
	DISASTER* CENCITY, γ_{017}			**-0.0093**	(0.0120)
Rate of Change	TIME, γ_{100}	0.0079***	(0.0005)	0.0078***	(0.0005)
	TIME*INCOME, γ_{110}	2.27E-9***	(0)	1.893E-9***	(0)
	Effect of Disaster on the Rate of Change				
	POSTTIME, γ_{120}	**-0.00047**	(0.0005)	**-0.0003**	(0.0006)
	POSTTIME*CENCITY, γ_{160}			**-0.0009**	(0.0011)
Variance Components					
Level1	Within-neighborhood, σ_e^2	0.0233***	(0.0002)	0.0233***	(0.0002)
Level2	In initial status, σ_0^2	0.0055***	(0.0004)	0.0054***	(0.0004)
	In rate of change, σ_1^2	5.45E-6***	(0)	5.44E-6***	(0)
	In DISASTER, σ_2^2	0.00029	(0.0003)	0.000271	(0.0003)
	In POSTTIME, σ_3^2	3.061E-6~	(2.04E-6)	2.942E-6~	(0.0002)
Goodness-of-Fit					
	Deviance	-28946.1		-28948.4	
	AIC	-28808.1		-28806.4	
	BIC	-28410.3		-28397.2	

- Dummy variables for each state and each major hurricane are omitted from this table (see A.2.12. Model Output for MODLE D_8 on Appendix)
~ p<.10; * p<.05; **p<.01; ***p<.001

metropolitan areas is -0.0093 (not statistically significant); (4) the estimated rate of change in DIVERSITY for the average neighborhoods without experience of a major natural disaster is 0.0078 (p < 0.001); (5) the estimated differential in the rate of change in DIVERSITY between neighborhoods with disaster experience and the others is -0.0003 (not statistically significant); and (6) of neighborhoods with major disaster experience, the estimated differential in the rate of change in DIVERSITY between neighborhoods in the central cities and other neighborhoods is -0.0009 (not statistically significant).

From the results, we find that neighborhoods that experience a natural disaster are likely to suffer from an instant decline in their racial diversity compared to neighborhoods without such experience and that neighborhoods in the central cities are likely to experience a larger decline in racial diversity than those in non-central cities. However, we cannot consider that the results definite because the estimated effects of DISASTER, DISASTER*CENCITY, POSTTIME, and POSTTIME*CENCITY are not statistically significant at the conventional confidence level.

The within-neighborhood variance component (σ_ε^2) for Model D_8 (0.0233) does not change from that of Model D_5. The between-neighborhoods variance components ((σ_0^2 and σ_1^2) for Model D_8 are also identical to those of Model D_5, indicating still explicable residual variations in both the initial status and the rate of change. The variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is 0.00027, but it is not statistically significant at the conventional confidence level. We do not reject the null hypothesis that the variance component in discontinuity in the elevation for DISASTER between neighborhoods (σ_2^2) is zero. Thus, we can conclude that DISASTER*CCITY effectively explains the differential effect of DISASTER on change in the initial status of the racial diversity trajectory among neighborhoods, reducing σ_2^2 by zero.

CHAPTER 6

CONCLUSIONS AND POLICY IMPLICATION

6.1. Findings

This dissertation links the extensive research in two distinct areas: natural hazards mitigation and neighborhood change. It focuses on how a natural disaster can interrupt the neighborhood change trajectory. The results of the analyses confirm the hypothesis that a natural disaster, as a "transient, exogenous shock", affects the trend of neighborhood change and intervenes in the path of change over time and that natural disasters alter neighborhoods differentially according to their basic characteristics. Furthermore, it suggested that these neighborhood changes, once accelerated by a natural disaster, further increase the socioeconomic and racial disparity of residential populations on a metropolitan neighborhood scale. The analysis also explored the association between natural disasters and neighborhood change and further examined the differential impact of natural disasters on neighborhood change, seeking to answer the following questions: (1) Does a natural disaster change the trend of neighborhood change? (2) Does the impact of a natural disaster on neighborhood change differ among neighborhoods? (3) Do natural disasters result in increasing disparity of populations at the neighborhood level, decreasing racial diversity within a neighborhood?

To answer these questions, this dissertation examined changes in the trends of metropolitan neighborhoods induced by five major hurricanes (Hurricane Allen in 1980, Hurricane Alicia in 1983; Hurricane Elena in 1985; Hurricane Gloria in 1985; Hurricane

Hugo in 1989), all of which caused serious damage between 1980 and 1990. To estimate the effects of intervention by these natural disasters on neighborhood change, it examined the trajectory of indicators of neighborhoods in the pre- and post-intervention periods, using the study period between 1970 and 2000. In the process, it controlled the census tracts in U.S. metropolitan counties that have never been affected by any major natural disasters, including hurricanes, from 1970 through 2000. In addition, this dissertation considered time after a natural disaster as a significant factor to measure the change in the impacts of the disaster according to time. More importantly, to carry out these analyses, it employed longitudinal models, "multilevel models for change," to examine the intervention effects of the hurricanes on neighborhood change (the level-1 model) and the differential effects according to the intensity of the hurricanes and the characteristics of neighborhoods (the level-2 model). This approach provided a more thorough understanding of the impact, both conceptually and methodologically, of the natural disasters.

First of all, the longitudinal model was tested to determine whether the model is more effective at tracking the neighborhood change trajectory over time than other models. Toward this effort, the outcome variation in neighborhood change was quantified in two important ways: across neighborhoods without regard to time (the unconditional means model or the ANOVA model), and across both neighborhoods and time (the unconditional growth model). The results helped us establish (1) whether or not systematic variation in neighborhood change worth exploring had occurred; and (2) where the variation reside (within or between neighborhoods).

The ANOVA models estimated the variance components for three key outcomes (i.e., home values, poverty rates, and racial diversity) of neighborhood change. Results of the ANOVA models clearly indicated significant variations in home values, poverty rates, and racial diversity both within neighborhoods and between neighborhoods. In particular, compared to the other two indicators, neighborhood home values exhibited larger variations both within neighborhoods and between neighborhoods. Of all the variations in home values, poverty rates, and racial diversity, about 88 percent, 66 percent, and 64 percent, respectively, were due to difference within neighborhood, which are generally caused by time. Thus, we concluded that the average neighborhood home value, poverty rates, and racial diversity vary over time and that neighborhoods differ with regard to the three indicators.

The unconditional growth model examined how the three indicators changed according to time, including the time predictor in the ANOVA model. The results showed that the home values, the poverty rates, and the racial diversity of neighborhoods increased between 1970 and 2000. For all of the indicators, variation within neighborhoods decreased, indicating that some parts of the within-neighborhood variation in the indicators are systematically associated with the passage of time. However, some important within-neighborhood variation still remained, and the variability in the initial status and the rates of change, which represent differences among neighborhoods, were also not zero. We understand that home values, poverty rates and racial diversity still differ not only within neighborhoods but also between neighborhoods. This finding indicates that it might be advantageous to (1) introduce some substantive predictors that reduce variability within neighborhoods and (2) explain heterogeneity among neighborhoods in each indicator.

One of the main research questions in this dissertation, whether a natural disaster affects the trend of neighborhood change, pertains to whether a natural disaster predictor can reduce variation in each neighborhood indicator within neighborhoods. To answer this question, this dissertation examined shifts in the neighborhood change trajectory before and after a natural disaster for the three indicators. For all of the indicators of neighborhood change, a discontinuity model that demonstrates changes in both the elevation and the slope for neighborhood change trajectories resulting from a natural disaster was employed to more effectively postulate a discontinuous neighborhood change trajectory resulting from the natural disasters. The results confirmed the hypothesis that natural disasters have a significant impact on the trend of neighborhood change, reducing variation in the indicators within neighborhoods.

The results can be summarized in three ways: (1) Natural disasters have a negative impact on the elevation of neighborhood change trajectories for home values, but a positive impact on the subsequent rate of change; (2) natural disasters cause an increase in the elevation of the neighborhood change trajectory for poverty rates and a decrease in the subsequent rate of change; and (3) although neighborhood racial diversity may not be affected by natural disasters in either the elevation or the rate of change of the neighborhood change trajectories (they are not statistically significant at the conventional confidence level), a variation in the rate of change by natural disasters among neighborhoods may still exist. These results strongly suggest that while home values are likely to immediately decrease after a natural disaster but not shift in the subsequent rate of change, poverty rates are likely to increase immediately in the aftermath of the disaster and to annually decline over time. Although the average neighborhood racial diversity trajectory is not likely to change in the aftermath of a natural disaster, the results of the longitudinal analysis show that changes in the elevation and the rate of change after a natural disaster tend to vary from neighborhood to neighborhood.

Finally, this dissertation examined whether the effects of natural disasters on neighborhood change trajectories differ among neighborhoods and determined that natural disasters affect the trend of neighborhood change differently according to (1) the magnitude of the natural disasters, (2) the socioeconomic conditions of neighborhoods, and (3) the political power of the local jurisdictions in which a neighborhood belongs. Longitudinal models were developed for each neighborhood change indicator, including predictors that explained heterogeneity among neighborhoods in the level-2 sub-models. The analyses confirmed the hypothesis of this dissertation, the differential effects on neighborhood change according to the intensity of a natural disaster, the average income of a neighborhood, and its location.

First, the differential effects of natural disasters on neighborhood change according to the intensity of the disasters were explored for the three key outcomes of neighborhood change. For two of these indicators (i.e., home values and poverty rates), the more intense the natural disaster is, the more adversely a neighborhood changes. Confirming the previous results of the analysis that neighborhoods that experience a natural disaster are more likely to undergo an immediate decline in their median home values that neighborhoods that do not experience one, it found that neighborhoods struck by more intense disasters are more likely to experience the rapid decline in home values than those struck by less intense disasters. In addition, neighborhoods that experience natural disasters tend to suffer an immediate increase in their poverty rates, but they experience annual decreases in their poverty rates after the disasters. In addition, neighborhoods by more intense disasters experience a more rapid increase in poverty rates that those struck by less intense disasters, and the former are more likely to experience an increase in racial diversity than the latter; however, the natural disasters themselves are likely to decrease racial diversity, while very intense natural disasters are likely to increase it.

Second, this dissertation explored how the shifts in neighborhood change trajectory caused by natural disasters differ according to neighborhood socio-economic characteristics. It found that such shifts were significantly associated with neighborhood socio-economic characteristics, especially income. Natural disasters appear to impact low- and high-income neighborhoods more adversely than they do moderate-income neighborhoods, and the impact on low-income neighborhoods is the most severe. Most importantly, the adverse impact on low-income neighborhoods was long lasting. The dissertation also showed that low- and high-income neighborhoods tend to experience the immediate decrease in median home values and racial diversity after a natural disaster, while moderate-income neighborhoods do not. However, home values and racial diversity in high-income neighborhoods tend to increase annually after the disaster and eventually recover their status. However, those of low-income neighborhoods tend to have more difficulty recovering their status, especially home values. In addition, while low-income neighborhoods experience the smallest increase. Therefore, we can conclude that the impact of natural disasters on neighborhoods with different socio-economic statuses varies and that low-income neighborhoods appear to be more vulnerable than other neighborhoods.

Third, neighborhoods located in the central cities of metropolitan areas tend to change differentially after a natural disaster compared to those in non-central cities. While home values of neighborhoods in non-central cities are likely to decrease after natural disasters, those in the central cities are likely to increase. In addition, the poverty rates in neighborhoods in non-central cities tend to increase immediately in the aftermath of a disaster, but the rate of change in the poverty rates tends to decreased annually after the disaster. On the other hand, poverty rates in central city neighborhoods are likely to decrease after the disaster. These results suggest that after a major natural disaster, neighborhoods in non-central cities, experiencing lower home values and higher poverty rates, suffer more severely than those in central cities. However, natural disasters appear not to have any impact on racial diversity in neighborhoods regardless of their location.

6.2. Discussion and Conclusion

The longitudinal analysis shows that the effects of a natural disaster on neighborhoods were generally negative and long lasting and furthermore that most of neighborhoods in the United States are not strongly resilient to the natural disaster. These findings are explained in detail as follows.

First, home value in a neighborhood immediately decreases in the aftermath of a natural disaster and does not return to pre-disaster levels in the long-term. These findings are not consistent with several postdisaster case studies, but are consistent with a recent empirical study about housing recovery after a natural disaster. Postdisaster case studies showed that overall average assessed single-family home values returned to pre-disaster levels within two years (Comerio 1998; Wu and Lindell 2004). However, the recent study using the panel data before and after Hurricane Andrew found that assessed sing-home values decreased one year after the hurricanes and the effects were still apparent two years after the hurricane. Therefore, the study concluded that home values take much longer than two years to return to pre-disaster values. Beyond this finding, this dissertation, examining the trend of neighborhood home value from 1970 and 2000, found that home values in a neighborhood affected by a major natural disaster do not recover to those in a non-disaster neighborhood even 15 years after the disaster.

Interestingly, this dissertation showed that neighborhoods with a more severe disaster experience tend to return more quickly to their prior status of home values than those with a less severe disaster experience although the former tend to suffer from a more rapid instant decline in home values. This finding agrees with Pais and Elliott's (2008) conclusion that home values in areas that experienced the greatest relative damage increase more ten years after a major hurricane compared to those in areas that experience the least damage Homes in neighborhoods that experienced a severe disaster are more likely to be completely demolished after the disaster compared to those in a neighborhood experienced only slight disaster. These homes are likely to be abandoned just after the disaster and to be rebuilt in the reconstruction and recovery process (Bolin and Stanford 1998b). Finally the values of new homes in the neighborhoods are similar with or greater than those of old home in the non-disaster neighborhoods.

Second, the poverty rate in a neighborhood affected by a natural disaster immediately increases, but recovers to that in a neighborhood not affected by the disaster in the long-term. After a natural disaster, people or households at the low end of socioeconomic status are more likely to experience severe economic hardship because they have smaller financial and/or economic capital at the time of the crisis (Chappell et al. 2007). Because low-income households without the insurance and other resources cannot afford to repair or rebuild their homes, they are more likely to abandon their home and to become homeless. In reality, the number of abandoned homes rapidly increases after a natural disaster (Zhang and Peacock 2010). Business disruption or fail in the surrounding areas also push the poor to be unemployed and get poorer and poorer. As a result, the poverty rate increases in the aftermath of the disaster. The fact that severely damaged businesses have difficulties returning to their prior status (Dalhamer and Tierney 1998) is also related to a more rapid increase and long lasting effect on poverty rates in neighborhoods with more intense disaster.

Third, a natural disaster increases racial and income disparity between low- and high-income neighborhoods. After a natural disaster, low-income neighborhoods experience a subsequent decrease in home values, a rapid increase in poverty rates and an immediate decrease in racial diversity, and suffer difficulties to return to its historical trend. On the other hand, high-income neighborhoods do not take too much time to recover their status and even are improved in the long-term (over 10-15 years after the disaster) although the neighborhoods experience an immediate decrease in home values and racial diversity and an increase in poverty rates just after the disaster. These findings are consistent with the natural hazard literature that income would have a positive effect on housing recovery. However, Zhang and Peacock (2010), investigating the recovery process of sing-family households in Miami-Dade County, Florida after Hurricane

Andrew, found that high-income neighborhoods experience a more rapid decline in home values than low-income neighborhoods one year after the hurricane. They concluded that hurricane damage reduced the difference in home values across neighborhoods of varied incomes. This may be because they just explored a change in home values for four years after the hurricane. The results of the longitudinal analyses in this dissertation showed that home values in high-income neighborhoods that experience a natural disaster have increased after the hurricane and are even higher than those in high-income neighborhood without a hazard experience in the long term. Finally the difference in home values between low- and high-income gets larger over time.

This adverse change in low-income neighborhoods after a natural disaster can be explained by the great disadvantage of the distribution of federal assistance in the neighborhoods during the reconstruction and recovery period. Government disaster aid plays an important role in recovering to their pre-impact level for low-income households. However, the literature found that recovery programs by the federal government were designed in ways that limited access to federal assistance in areas with high percentage of low-income households (Bolin and Stanford 1998a 1998b; Fothergill and Peek 2004; Loukaitou-Sideris and Kamel 2004; Peacock et al. 1997; Quanrantelli 1999). Without assistance, low-income neighborhoods that cannot afford to repair their homes or to arrange financing for their rehabilitation are more likely to experience demolition of their neighborhoods than high-income neighborhoods (Comerio et al. 1994; Bolin and Stanford 1998b).

Fourth, neighborhoods in non-central cities recovered more slowly than those in central cities, leaving them relatively worse off in the long term. This dissertation found that neighborhoods in non-central cities experience a rapid decrease in home values and a greater increase in poverty rates compared to those in central cities and that the adverse effects continue in the long term. The difference in recovery outcomes across municipalities may be related to the role of the municipalities in receiving larger sharing of federal assistance (Kamel and Loukaiou-Sideris 2004). The findings of post-disaster case studies confirm the significant role a municipality plays in the recovery outcomes of its residents and neighborhoods (Bolin and Stanford 1998a; Dash et al. 1997; Pais and Elliott 2008). In particular, Bolin and Stanford (1998a) examined the recovery and reconstruction processes after Northridge earthquake in the two municipalities and found that the poor rural municipality was forced to construct low-income housing units to tide the residents over during a regional affordable housing crisis and that low-income families concentrated in the municipality. These findings provide some evidence to interpret the results of the analyses in this dissertation, regarding the differential effects of a natural disaster on neighborhood change according to municipality. Non-central cities are more likely to have smaller population, smaller staffs and fewer resources to deal with a natural disaster than central cities. Even non-central cities are more likely to receive smaller share of federal assistance. In addition, the stronger demand for housing in the central city location may be related to fewer declines in home values in the area compared to those in non-central cities. As a result, neighborhoods in non-central cities tend to suffer hardships and find it more difficult to recover to their prior status, experiencing continuous decrease in home values and increase in poverty rates in the long term.

The hazard literature has argued that natural disasters provide the impetus for major changes or alterations in the structures of impacted social system and that the disaster accelerate (or decelerate) preexisting trends often grounded in historical cultural framework (Bates 1982; Bates et al. 1963; Dacy and Kunreuther 1969; Peacock and Bates 1984). The findings of this dissertation indicate that a natural disaster at least affects a change in neighborhood (on the micro level). A major natural disaster changes the historical trend of neighborhood change. The neighborhood change induced by the natural disaster results in increasing pre-disaster disparity among neighborhoods─between low-and high-income neighborhoods, and between central city neighborhoods and non-central city neighborhoods. In particular, the changes that take place in high-income neighborhoods after a natural disaster differ from those that occur in low-income neighborhoods; that is, while high-income neighborhoods grow and improve, low-income neighborhoods decline. In addition, neighborhoods that are more strongly affected by disasters undergo migration patterns that differ from those in surrounding neighborhoods. Thus, the keys to greater awareness of the long-term impact of neighborhoods are the accurate identification of the intensity of the natural disasters and the stratification of neighborhoods according to key factors that have a significant impact on recovery outcomes in the aftermath of the natural disasters.

As with all research, the analyses in this dissertation contain several limitations. The first and most obvious is that it examined data from only four hurricanes. Although these data allowed a close inspection of the effects of hurricanes on various types of neighborhood characteristics, future research will benefit from analyses that extend beyond these disasters by considering cross-national comparisons and analyses of recovery from other natural disasters such as earthquakes and floods.

Second, this dissertation explored the shift in the neighborhood change trajectory caused by natural disasters during four time points (1970, 1980, 1990, and 2000), two before and two after the disasters. Using longitudinal data, it effectively estimated the trend of neighborhood change and also determined the interruption effects of the disasters. Although the four time points were sufficient for the longitudinal data analysis, with more time points, researchers could perform a more thorough, precise investigation of the effects of natural disasters on neighborhood change. In addition, because decennial census data may not allow researchers to pinpoint immediate shifts in the neighborhood change trajectory after a disaster, shorter-term data should be accessed and employed to more effectively track neighborhood change.

6.3. Policy Implications

A change in the social system after a natural disaster stems from two factors outside the system: the disaster itself and the rehabilitation process (Base et al., 1963). This dissertation introduced these outside factors into the neighborhoods, producing changes in the characteristics. From the longitudinal analyses, this dissertation concludes that a natural disaster acts as an intervention in the normal time series of neighborhood change. The intervention upsets a neighborhood and then accelerates change. The impacts are long lasting. In particular, low-income and non-central city neighborhoods tend to sustain more adverse change after a natural disaster, and the adverse effects may have continue for a long time after the disaster.

It is said that a natural hazard open a "window of opportunity" for creating more resilient communities. The reconstruction process could be used as an opportunity to increase the neighborhood's resilience to future disasters. However, the findings of this dissertation showed that neighborhoods in the United States are less likely to be resilient to a natural disaster, taking long time to recover to their pre-disaster trend of neighborhood change. It indicates that governments have failed to create more resilient communities when a window opens.

This failure in creating community resilience is related to two kinds of tensions that play out through the recovery process: tension between the need for "speed and deliberation" (Olshansky and Johnson 2010; Olshansky et al. 2008) and tension between "the relative weight affordable professional and resident assessments and priorities in setting recovery agenda" (Nelson et al. 2007, p. 23). Following a natural disaster, governments often focus on quickly rebuilding neighborhoods, rather than actions necessary to craft credible programs and policies to ensure safe and equitable rebuilding. Furthermore, local governments tend to miss an opportunity to participate with residents in a discussion about the difficult decisions the city had to make to reduce risk and facilitate an equitable and efficient recovery. The failure can result in increasing long-term vulnerability of affected neighborhoods.

Then, how can we plan for more resilient places that are less vulnerable to future disasters? This dissertation suggested that neighborhood change can be promoted by "the disaster itself" and "the rehabilitation process". We acknowledge that the distribution of damage caused by a natural disaster is not significantly associated with any particular neighborhoods or socio-economic characteristics. Therefore, this dissertation suggests policies, more focusing on “the rehabilitation process,” which includes the distribution of federal recovery funds and more effective reconstruction programs.

First, to take advantage of an open window, a community should have a recovery plan in place long before a disaster strikes (“predisaster planning for postdisaster recovery” (Passerini 2000)). A recovery plan includes short-range emergency and rehabilitation actions (temporary housing, damage assessment, debris removal, restoration of utilities, reoccupancy permitting, reconstruction priorities) and long-range redevelopment decisions (building moratoria, replanning of stricken areas, relocation of housing to safer sites). The communities with a recovery plan are better able to effect change and recover well after a natural disaster. Without a predisaster plan, relocation and reconstruction are harder and take longer.

Findings from this dissertation underscore the importance of a recovery plan that effectively responds to the adverse effects of natural disasters on neighborhood change. This dissertation found that neighborhoods immediately change after natural disasters, and that neighborhood change caused by disasters is long lasting. More importantly, the long-term effects are more adverse in low-income and non-central city neighborhoods. Thus, local governments should be encouraged to develop a recovery plan not only that ensure an immediate response in the aftermath of a natural disaster but also that ensure rebuilding and rehabilitation processes in the short-, mid- and long-term. The recovery plan should also include discussions on the various policies to reflect the differential effects of a natural disaster on neighborhood change according to the characteristics of a neighborhood. The policies include identification of location of vulnerable population, supply of affordable housing, building a facility or programs to educate residents, or development of a comprehensive program to stimulate opportunities for families to retain their home or become homeowners. Through the recovery plan, planners can more systematically implement the policies.

Second, the most important focus of the rehabilitation after a natural disaster should be on the equal distribution of recovery resources among neighborhoods and municipalities; that is, the purpose should be to minimize the adverse effects of the rehabilitation process on neighborhood change. Many case studies after natural disasters and empirical studies found that post-disaster recovery processes contain discriminatory practices in not only the distribution of assistance, but also the design process to "reproduce a particular social order and rely on definitions of social justice that are tailored to the ruling interests" (Kamel and Loukaiou-Sideris 2004, p.536). In particular, the reconstruction and recovery processes of New Orleans regions struck by Hurricane Katrina showed that most of the loans approved for reconstruction after disaster went to families in affluent communities while only a small portion went to families residing in poor neighborhoods (Taylor and Silver 2006). As a result, residents of low-income neighborhoods have suffered from much longer than those of higher-income neighborhoods. Kamel and Loukaitou-Sideris (2004), examining the effects of the distribution of federal assistance on the outcome of long-term recovery from the Northridge Earthquake, found that the distribution of federal assistance and consequently the potential for recovery from the earthquake was strongly associated with particular socio-demographic characteristics of households and neighborhoods. Thus, residents who have limited local resources before a disaster suffer even more when federal programs fail to provide sufficient funds and external assistance is limited, which exacerbate their recovery relative to others that have sustained similar or less damage.

In addition, the distribution of federal assistance varies across municipalities depending on the response capacity of municipalities, which can profoundly influence the long-term consequences of a natural disaster on their neighborhoods. The political and economic conditions of local municipalities produce differential outcomes in the recovery and reconstruction processes after a natural disaster (Boin and Stanford 1998a). For example, the poor rural municipality was forced to construct low-income housing units to tide its residents over during a regional affordable housing crisis.

Considering the findings of this dissertation, that natural disasters more adversely affect low-income neighborhoods and non-central city neighborhoods, planners and policy makers, whether at the local, state, or federal level, should pay more careful attention to the reconstruction and recovery process in such neighborhoods and develop programs that channel more financial support to these neighborhoods. Some researchers point to a limitation of the current approach, one of the main reasons for the unequal distribution of recovery assistance: the allocation of assistance based on absolute losses rather than emergency needs (Kamel and Loukaiou-Sideris, 2004). Federal programs for residential assistance take into account a combination of residential damage and the available resources of applicants in order to direct resources where they are most needed. Even though low- and high-income neighborhoods suffer from the similar physical damage from the disasters, the rehabilitation of the former is likely to extend over a longer than desired period without adequate assistance. Slower recovery in these neighborhoods can result in neighborhood deterioration. However, a new approach that provides prompt and adequate assistance that facilitates a return to a status prior to a disaster could play a critical role in minimizing the adverse effects on these neighborhoods.

In addition, the research approach using a longitudinal analysis can be applied to other disruptive impacts beyond natural disasters. Governments can adopt the approach to investigate the impact of an implemented policy such as CDBG, or a different type of disruptive impact, such as a factory closing or construction of public housing, on the surrounding areas. For example, local government built public housing in a certain area to provide affordable housing and then tried to examine the impact of the public housing on the surrounding neighborhoods. Using the research approach in this dissertation, planners can understand that the introduction of public housing can act as an intervention in the normal time series of neighborhood change, and that the intervention eventually upsets the neighborhood and then accelerates neighborhood change. And then they can effectively analyze the intervention impact of the public housing on neighborhood change, excluding the underlying mechanism of neighborhood change. Therefore, the approach can help planners to examine the impact of policies or issues regarding planning on neighborhood (or city) change over time.

APPENDIX A

SAMPLES

Table A-1. Number of Census Tracts for Treatment Group, by Counties Affected by Natural Disaster in the 1980s

State	FIPS	County	Total Number of Census Tracts	Number of Census Tracts for 30% Sample
Connecticut	09001	Fairfield	209	69
	09003	Hartford	221	74
	09007	Middlesex	30	10
	09009	New Haven	185	62
	09011	New London	60	20
	09013	Tolland	27	9
Delaware	10001	Kent	34	11
	10003	New Castle	127	43
Louisiana	22073	Ouachita	41	14
Maine	23019	Penobscot	26	8
Massachusetts	25001	Barnstable	37	12
	25003	Berkshire	23	8
	25005	Bristol	116	39
	25013	Hampden	92	30
	25017	Middlesex	297	99
	25021	Norfolk	121	41
	25023	Plymouth	91	30
	25025	Suffolk	176	59
	25027	Worcester	157	52
Mississippi	28045	Hancock	6	2
	28073	Lamar	6	2
New Hampshire	33011	Hillsborough	74	24
New Jersey	34001	Atlantic	62	21
	34003	Bergen	163	54
	34005	Burlington	119	40
	34007	Camden	140	47
	34009	Cape May	24	8
	34011	Cumberland	34	11
	34013	Essex	212	71
	34015	Gloucester	59	19
	34017	Hudson	158	53
	34019	Hunterdon	26	9
	34021	Mercer	73	24
	34023	Middlesex	177	59
	34025	Monmouth	141	47
	34027	Morris	99	33
	34029	Ocean	116	39
	34031	Passaic	85	28
	34033	Salem	24	8

Table A-1. Continued

State	FIPS	County	Total Number of Census Tracts	Number of Census Tracts for 30% Sample
New Jersey	34035	Somerset	62	21
	34039	Union	106	35
New York	36005	Bronx	355	119
	36027	Dutchess	66	22
	36047	Kings	783	261
	36059	Nassau	274	92
	36071	Orange	67	22
	36079	Putnam	19	7
	36081	Queens	671	224
	36083	Rensselaer	41	15
	36085	Richmond	110	37
	36087	Rockland	58	19
	36103	Suffolk	313	104
	36119	Westchester	221	74
North Carolina	37003	Alexander	7	2
	37025	Cabarrus	21	7
	37027	Caldwell	14	4
	37035	Catawba	28	10
	37059	Davie	7	2
	37071	Gaston	44	15
	37109	Lincoln	12	4
	37119	Mecklenburg	144	48
	37159	Rowan	28	9
	37179	Union	17	6
	37197	Yadkin	7	2
Pennsylvania	42017	Bucks	136	45
	42045	Delaware	147	49
	42101	Philadelphia	381	127
Rhode Island	44001	Bristol	11	4
	44003	Kent	37	12
	44007	Providence	138	46
	44009	Washington	25	9
South Carolina	45015	Berkeley	22	7
	45019	Charleston	78	26
	45021	Cherokee	9	3
	45035	Dorchester	17	6
	45063	Lexington	43	14
	45079	Richland	72	24
	45083	Spartanburg	14	5
	45085	Sumter	22	7
	45091	York	35	12
Texas	48039	Brazoria	45	15
	48041	Brazos	30	10
	48061	Cameron	86	29
	48157	Fort Bend	58	19
	48167	Galveston	61	20
	48199	Hardin	11	4
	48215	Hidalgo	80	27
	48245	Jefferson	70	24

Table A-1. Continued

State	FIPS	County	Total Number of Census Tracts	Number of Census Tracts for 30% Sample
Texas	48361	Orange	20	7
	48479	Webb	32	11
Virginia	51073	Gloucester	5	2
	51115	Mathews	2	0
	51199	York	13	4
	51735	Poquoson City	3	1
West Virginia	54107	Wood	27	9
TOTAL Number		95	9,073	3,028

APPENDIX B

MODEL OUTPUTS

B.1. Model Output for MODEL H_5: the Effects of Natural Disasters on Neighborhood Home Values (Table 5-11on p. 128)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	74251.30507145	
1	4	72136.13606087	.
2	1	71984.10581780	.
3	1	71896.61456633	0.00530262
4	1	71858.98939423	0.00134801
5	1	71850.13359717	.
6	1	71849.33621509	0.00000167
7	1	71849.32662466	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.09982	0.006398	15.60	<.0001
TIME	GEO2000	0.000062	6.438E-6	9.59	<.0001
DISASTER	GEO2000	0.03541	0.008378	4.23	<.0001
POSTTIME	GEO2000	0.000012	0.000031	0.39	0.3487
Residual		0.4820	0.003993	120.72	<.0001

Fit Statistics

-2 Log Likelihood	71849.3
AIC (smaller is better)	71987.3
AICC (smaller is better)	71987.6
BIC (smaller is better)	72385.0

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	8.0903	0.1907	2296	42.42	<.0001
TIME	0.04899	0.002014	2313	24.33	<.0001
TIME*INCOME	-1.32E-6	0	28E3	-Infty	<.0001
DISASTER	-0.07661	0.03351	332	-2.29	0.0229
POSTTIME	0.002554	0.002361	279	1.08	0.2803
INCOME	0.000051	0	28E3	Infty	<.0001
NEWHOME	-0.09521	0.03288	28E3	-2.90	0.0038
OLDHOME	-0.2807	0.02077	28E3	-13.51	<.0001
WHITE	0.3173	0.02093	28E3	15.16	<.0001

B.1. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
HISPANIC	-0.5645	0.03965	28E3	-14.24	<.0001
M_POP	1.055E-8	0	28E3	Infty	<.0001
M_INC	8.596E-6	1.337E-6	28E3	6.43	<.0001
M_UEMP	-0.06293	0.03856	28E3	-1.63	0.1027
R_POP	19.6261	0.8590	28E3	22.85	<.0001
NATURAL	0.02601	0.006452	28E3	4.03	<.0001
CBD	-0.1532	0.01624	28E3	-9.43	<.0001
HIGHWAY	0.001539	0.001263	28E3	1.22	0.2228
HUGO	0.05302	0.1678	28E3	0.32	0.7520
ELENA	-0.3546	0.3047	28E3	-1.16	0.2446
ALICIA	0.1479	0.1538	28E3	0.96	0.3364
GLORIA	0.1812	0.09925	28E3	1.83	0.0679
ALLEN	0.3793	0.2110	28E3	1.80	0.0723
STATE_AZ	0.6715	0.1907	28E3	3.52	0.0004
STATE_AR	0.4164	0.1949	28E3	2.14	0.0326
STATE_CA	0.9022	0.1917	28E3	4.71	<.0001
STATE_CO	0.6909	0.1901	28E3	3.63	0.0003
STATE_CT	0.7374	0.2145	28E3	3.44	0.0006
STATE_DC	0.8869	0.3763	28E3	2.36	0.0184
STATE_DE	0.2452	0.3239	28E3	0.76	0.4490
STATE_FL	0.4081	0.2005	28E3	2.04	0.0418
STATE_GA	0.3727	0.2292	28E3	1.63	0.1039
STATE_ID	0.1887	0.2808	28E3	0.67	0.5016
STATE_IL	0	.	.	.	.
STATE_IN	0.1276	0.5418	28E3	0.24	0.8138
STATE_KY	0.4499	0.2163	28E3	2.08	0.0375
STATE_LA	0.6474	0.2434	28E3	2.66	0.0078
STATE_MD	0.7557	0.2071	28E3	3.65	0.0003
STATE_ME	0.04103	0.4248	28E3	0.10	0.9231
STATE_MA	0.3697	0.2313	28E3	1.60	0.1100
STATE_MI	0.5401	0.2470	28E3	2.19	0.0288
STATE_MN	0.6515	0.3055	28E3	2.13	0.0330
STATE_MS	0.4903	0.3581	28E3	1.37	0.1710
STATE_MO	0.3722	0.2538	28E3	1.47	0.1424
STATE_MT	-0.1724	0.2585	28E3	-0.67	0.5048
STATE_NE	0	.	.	.	.
STATE_NH	0.8776	0.3587	28E3	2.45	0.0144
STATE_NV	0.5132	0.2698	28E3	1.90	0.0572
STATE_NJ	0.6679	0.2207	28E3	3.03	0.0025
STATE_NM	0.4481	0.2348	28E3	1.91	0.0563
STATE_NY	0.5754	0.2087	28E3	2.76	0.0058
STATE_NC	0.3901	0.2672	28E3	1.46	0.1444
STATE_OH	0.6659	0.2081	28E3	3.20	0.0014
STATE_OK	0.2617	0.2190	28E3	1.20	0.2320
STATE_OR	0.5792	0.2188	28E3	2.65	0.0081
STATE_PA	0.5598	0.1971	28E3	2.84	0.0045
STATE_RI	0.4757	0.2747	28E3	1.73	0.0833
STATE_SC	0.4279	0.2372	28E3	1.80	0.0713
STATE_SD	0.1913	0.4059	28E3	0.47	0.6374
STATE_TN	0.6121	0.2034	28E3	3.01	0.0026
STATE_TX	0.4105	0.1988	28E3	2.06	0.0390
STATE_UT	0.7661	0.2637	28E3	2.91	0.0037
STATE_VT	0	.	.	.	.
STATE_VA	0.6137	0.2093	28E3	2.93	0.0034
STATE_WA	0.6769	0.2129	28E3	3.18	0.0015
STATE_WI	0.7190	0.2265	28E3	3.17	0.0015
STATE_WY	-0.1886	0.3299	28E3	-0.57	0.5675
STATE_WV	0.4764	0.2463	28E3	1.93	0.0531

B.2. Model Output for MODEL P_5: the Effects of Natural Disasters on Neighborhood Poverty Rates (Table 5-12 on p. 132)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	-83104.38941233	
1	4	-85636.52703777	.
2	1	-85737.95857167	0.00034193
3	1	-85768.90910175	0.00006781
4	2	-85774.59849152	0.00000350
5	1	-85774.87224857	0.00000003
6	1	-85774.87421378	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.000408	0.000061	6.66	<.0001
TIME	GEO2000	2.012E-6	0	.	.
DISASTER	GEO2000	0.000197	0.000084	2.34	0.0097
POSTTIME	GEO2000	0	.	.	.
Residual		0.004553	0.000036	124.84	<.0001

Fit Statistics

-2 Log Likelihood	-85774.9
AIC (smaller is better)	-85638.9
AICC (smaller is better)	-85638.6
BIC (smaller is better)	-85246.9

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	0.3811	0.01733	2306	22.00	<.0001
TIME	0.002357	0.000209	2331	11.28	<.0001
TIME*INCOME	6.823E-8	0	29E3	Infty	<.0001
DISASTER	0.03156	0.003116	338	10.13	<.0001
POSTTIME	-0.00174	0.000235	305	-7.41	<.0001
INCOME	-3.24E-6	0	29E3	-Infty	<.0001
NEWHOME	-0.02136	0.003098	29E3	-6.89	<.0001
OLDHOME	0.06129	0.001934	29E3	31.70	<.0001
WHITE	-0.2071	0.001946	29E3	-106.44	<.0001
HISPANIC	0.1882	0.003621	29E3	51.97	<.0001

B.2. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
M_POP	-736E-12	0	29E3	-Infty	<.0001
M_INC	-1.66E-6	0	29E3	-Infty	<.0001
M_UEMP	0.001469	0.003621	29E3	0.41	0.6850
R_POP	-0.2799	0.07662	29E3	-3.65	0.0003
NATURAL	0.000186	0.000572	29E3	0.32	0.7457
CBD	0.009328	0.001396	29E3	6.68	<.0001
HIGHWAY	-0.00032	0.000114	29E3	-2.82	0.0049
HUGO	0.02363	0.01270	29E3	1.86	0.0627
ELENA	0.03457	0.02378	29E3	1.45	0.1460
ALICIA	0.001540	0.01112	29E3	0.14	0.8898
GLORIA	-0.00418	0.007304	29E3	-0.57	0.5668
ALLEN	0.1250	0.01505	29E3	8.31	<.0001
STATE_AZ	-0.04622	0.01732	29E3	-2.67	0.0076
STATE_AR	-0.03091	0.01771	29E3	-1.75	0.0809
STATE_CA	-0.05608	0.01740	29E3	-3.22	0.0013
STATE_CO	-0.04913	0.01727	29E3	-2.84	0.0044
STATE_CT	-0.06893	0.01876	29E3	-3.67	0.0002
STATE_DC	-0.1264	0.02745	29E3	-4.61	<.0001
STATE_DE	-0.04479	0.02571	29E3	-1.74	0.0815
STATE_FL	-0.02304	0.01782	29E3	-1.29	0.1958
STATE_GA	-0.00197	0.02003	29E3	-0.10	0.9215
STATE_ID	-0.03431	0.02388	29E3	-1.44	0.1509
STATE_IL	0	.	.	.	.
STATE_IN	-0.04205	0.05514	29E3	-0.76	0.4457
STATE_KY	-0.01820	0.01929	29E3	-0.94	0.3455
STATE_LA	-0.01135	0.02080	29E3	-0.55	0.5853
STATE_MD	-0.05688	0.01825	29E3	-3.12	0.0018
STATE_ME	-0.05231	0.03280	29E3	-1.59	0.1107
STATE_MA	-0.06444	0.01965	29E3	-3.28	0.0010
STATE_MI	-0.06351	0.02123	29E3	-2.99	0.0028
STATE_MN	-0.06839	0.02378	29E3	-2.88	0.0040
STATE_MS	-0.01758	0.03158	29E3	-0.56	0.5777
STATE_MO	-0.05258	0.02149	29E3	-2.45	0.0144
STATE_MT	-0.04315	0.02217	29E3	-1.95	0.0516
STATE_NE	0	.	.	.	.
STATE_NH	-0.05029	0.02876	29E3	-1.75	0.0803
STATE_NV	-0.08046	0.02226	29E3	-3.62	0.0003
STATE_NJ	-0.07064	0.01900	29E3	-3.72	0.0002
STATE_NM	-0.07080	0.02045	29E3	-3.46	0.0005
STATE_NY	-0.07194	0.01834	29E3	-3.92	<.0001
STATE_NC	-0.08632	0.02236	29E3	-3.86	0.0001
STATE_OH	-0.05873	0.01837	29E3	-3.20	0.0014
STATE_OK	-0.03469	0.01918	29E3	-1.81	0.0705
STATE_OR	-0.03310	0.01901	29E3	-1.74	0.0816
STATE_PA	-0.06873	0.01760	29E3	-3.91	<.0001
STATE_RI	-0.04804	0.02244	29E3	-2.14	0.0323
STATE_SC	-0.04284	0.02028	29E3	-2.11	0.0346
STATE_SD	-0.05139	0.03287	29E3	-1.56	0.1179
STATE_TN	-0.01656	0.01817	29E3	-0.91	0.3620
STATE_TX	-0.04127	0.01776	29E3	-2.32	0.0201
STATE_UT	-0.03887	0.02138	29E3	-1.82	0.0691
STATE_VT	0	.	.	.	.
STATE_VA	-0.05817	0.01857	29E3	-3.13	0.0017
STATE_WA	-0.05559	0.01862	29E3	-2.98	0.0028
STATE_WI	-0.07825	0.01957	29E3	-4.00	<.0001
STATE_WY	-0.06952	0.02967	29E3	-2.34	0.0191
STATE_WV	-0.05458	0.02156	29E3	-2.53	0.0114

B.3. Model Output for MODEL D_5: the Effects of Natural Disasters on Neighborhood Racial Diversity (Table 5-13 on p. 136)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	-25164.60692643	
1	2	-28787.37724866	0.00204935
2	1	-28906.57911341	0.00065215
3	1	-28942.20644015	0.00007633
4	1	-28945.99916313	0.00000114
5	1	-28946.05222532	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.005465	0.000369	14.79	<.0001
TIME	GEO2000	5.445E-6	0	.	.
DISASTER	GEO2000	0.000292	0.000276	1.06	0.1451
POSTTIME	GEO2000	3.061E-6	2.036E-6	1.50	0.0663
Residual		0.02331	0.000186	125.19	<.0001

Fit Statistics

-2 Log Likelihood	-28946.1
AIC (smaller is better)	-28808.1
AICC (smaller is better)	-28807.8
BIC (smaller is better)	-28410.3

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	0.5656	0.04379	2306	12.92	<.0001
TIME	0.007859	0.000451	2331	17.44	<.0001
TIME*INCOME	2.265E-9	0	29E3	Infty	<.0001
DISASTER	-0.00953	0.006470	338	-1.47	0.1419
POSTTIME	-0.00047	0.000544	305	-0.87	0.3837
INCOME	-7.74E-7	0	29E3	-Infty	<.0001
NEWHOME	0.01681	0.007068	29E3	2.38	0.0174
OLDHOME	0.01302	0.004396	29E3	2.96	0.0030
WHITE	-0.3496	0.004430	29E3	-78.91	<.0001
HISPANIC	0.6484	0.008345	29E3	77.70	<.0001
M_POP	-1.31E-9	0	29E3	-Infty	<.0001

B.3. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
M_INC	-4.26E-7	0	29E3	-Infty	<.0001
M_UEMP	-0.06062	0.008704	29E3	-6.97	<.0001
R_POP	-0.08584	0.1829	29E3	-0.47	0.6389
NATURAL	-0.01029	0.001470	29E3	-7.01	<.0001
CBD	-0.02967	0.003688	29E3	-8.05	<.0001
HIGHWAY	-0.00193	0.000284	29E3	-6.80	<.0001
HUGO	-0.01232	0.03909	29E3	-0.32	0.7527
ELENA	0.01628	0.07126	29E3	0.23	0.8193
ALICIA	0.03844	0.03506	29E3	1.10	0.2729
GLORIA	0.06024	0.02295	29E3	2.62	0.0087
ALLEN	-0.4021	0.04901	29E3	-8.20	<.0001
STATE_AZ	-0.06924	0.04385	29E3	-1.58	0.1144
STATE_AR	-0.07922	0.04478	29E3	-1.77	0.0769
STATE_CA	0.04801	0.04408	29E3	1.09	0.2760
STATE_CO	-0.08569	0.04373	29E3	-1.96	0.0500
STATE_CT	-0.09636	0.04935	29E3	-1.95	0.0509
STATE_DC	-0.1743	0.08721	29E3	-2.00	0.0457
STATE_DE	-0.02307	0.07533	29E3	-0.31	0.7595
STATE_FL	-0.01964	0.04626	29E3	-0.42	0.6712
STATE_GA	0.08802	0.05287	29E3	1.66	0.0960
STATE_ID	-0.1139	0.06567	29E3	-1.73	0.0830
STATE_IL	0	.	.	.	.
STATE_IN	-0.2670	0.1284	29E3	-2.08	0.0375
STATE_KY	-0.1467	0.05009	29E3	-2.93	0.0034
STATE_LA	0.05902	0.05635	29E3	1.05	0.2949
STATE_MD	-0.04916	0.04778	29E3	-1.03	0.3035
STATE_ME	-0.2270	0.09632	29E3	-2.36	0.0185
STATE_MA	-0.1785	0.05332	29E3	-3.35	0.0008
STATE_MI	-0.1002	0.05738	29E3	-1.75	0.0808
STATE_MN	-0.1276	0.07017	29E3	-1.82	0.0689
STATE_MS	0.05632	0.08411	29E3	0.67	0.5031
STATE_MO	-0.1201	0.05884	29E3	-2.04	0.0413
STATE_MT	-0.02366	0.05979	29E3	-0.40	0.6923
STATE_NE	0	.	.	.	.
STATE_NH	-0.2596	0.08279	29E3	-3.14	0.0017
STATE_NV	0.06094	0.06248	29E3	0.98	0.3294
STATE_NJ	-0.1064	0.05086	29E3	-2.09	0.0364
STATE_NM	-0.2211	0.05448	29E3	-4.06	<.0001
STATE_NY	-0.1262	0.04815	29E3	-2.62	0.0088
STATE_NC	0.002080	0.06175	29E3	0.03	0.9731
STATE_OH	-0.1483	0.04809	29E3	-3.08	0.0021
STATE_OK	0.02490	0.05061	29E3	0.49	0.6227
STATE_OR	-0.08502	0.05060	29E3	-1.68	0.0930
STATE_PA	-0.1297	0.04543	29E3	-2.85	0.0043
STATE_RI	-0.2071	0.06352	29E3	-3.26	0.0011
STATE_SC	0.09544	0.05494	29E3	1.74	0.0824
STATE_SD	0.05102	0.09489	29E3	0.54	0.5908
STATE_TN	-0.05937	0.04696	29E3	-1.26	0.2061
STATE_TX	-0.06000	0.04583	29E3	-1.31	0.1905
STATE_UT	-0.1048	0.06071	29E3	-1.73	0.0844
STATE_VT	0	.	.	.	.
STATE_VA	-0.02644	0.04822	29E3	-0.55	0.5835
STATE_WA	-0.02957	0.04922	29E3	-0.60	0.5480
STATE_WI	-0.1694	0.05242	29E3	-3.23	0.0012
STATE_WY	-0.08948	0.07790	29E3	-1.15	0.2507
STATE_WV	-0.1646	0.05721	29E3	-2.88	0.0040

B4. Model Output for MODEL H_6: the Differential Effect of Natural Disasters on Neighborhood Home Values According to the Intensity of Natural Disasters (Table 5-14 on p. 139)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	74110.49836685	
1	4	72005.77449793	.
2	1	71851.35354784	.
3	1	71762.42893928	0.00544386
4	1	71724.07145513	0.00139630
5	1	71714.95794650	.
6	1	71714.10403339	0.00000197
7	1	71714.09279308	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.09959	0.006389	15.59	<.0001
TIME	GEO2000	0.000062	6.462E-6	9.56	<.0001
DISASTER	GEO2000	0.03616	0.008482	4.26	<.0001
POSTTIME	GEO2000	0.000013	0.000032	0.42	0.3389
Residual		0.4808	0.003986	120.63	<.0001

Fit Statistics

-2 Log Likelihood	71714.1
AIC (smaller is better)	71856.1
AICC (smaller is better)	71856.4
BIC (smaller is better)	72265.3

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	8.0882	0.1905	2294	42.45	<.0001
TIME	0.04911	0.002013	2313	24.39	<.0001
TIME*INCOME	-1.32E-6	0	28E3	-Infty	<.0001
DISASTER	-0.05309	0.03467	331	-1.53	0.1267
DISASTER*INTENS_O	-1.2079	0.4583	28E3	-2.64	0.0084
POSTTIME	0.001014	0.002422	279	0.42	0.6757
INTENS_O*POSTTIME	0.1245	0.05172	28E3	2.41	0.0160
INCOME	0.000051	0	28E3	Infty	<.0001
NEWHOME	-0.09388	0.03285	28E3	-2.86	0.0043
OLDHOME	-0.2789	0.02076	28E3	-13.44	<.0001
WHITE	0.3189	0.02092	28E3	15.24	<.0001
HISPANIC	-0.5623	0.03968	28E3	-14.17	<.0001
M_POP	1.067E-8	0	28E3	Infty	<.0001
M_INC	8.495E-6	1.336E-6	28E3	6.36	<.0001
M_UEMP	-0.06257	0.03852	28E3	-1.62	0.1043
R_POP	19.6237	0.8581	28E3	22.87	<.0001

B.4. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
NATURAL	0.02612	0.006445	28E3	4.05	<.0001
CBD	-0.1532	0.01623	28E3	-9.44	<.0001
HIGHWAY	0.001511	0.001261	28E3	1.20	0.2309
HUGO	0.05921	0.1676	28E3	0.35	0.7239
ELENA	-0.3575	0.3044	28E3	-1.17	0.2402
ALICIA	0.1477	0.1537	28E3	0.96	0.3366
GLORIA	0.1785	0.09915	28E3	1.80	0.0718
ALLEN	0.3747	0.2109	28E3	1.78	0.0756
STATE_AZ	0.6715	0.1905	28E3	3.52	0.0004
STATE_AR	0.4166	0.1946	28E3	2.14	0.0323
STATE_CA	0.9019	0.1915	28E3	4.71	<.0001
STATE_CO	0.6912	0.1899	28E3	3.64	0.0003
STATE_CT	0.7438	0.2143	28E3	3.47	0.0005
STATE_DC	0.8882	0.3759	28E3	2.36	0.0181
STATE_DE	0.2457	0.3236	28E3	0.76	0.4477
STATE_FL	0.4084	0.2003	28E3	2.04	0.0415
STATE_GA	0.3733	0.2289	28E3	1.63	0.1029
STATE_ID	0.1889	0.2805	28E3	0.67	0.5007
STATE_IL	0	.	.	.	.
STATE_IN	0.1280	0.5413	28E3	0.24	0.8131
STATE_KY	0.4502	0.2161	28E3	2.08	0.0372
STATE_LA	0.6483	0.2432	28E3	2.67	0.0077
STATE_MD	0.7566	0.2069	28E3	3.66	0.0003
STATE_ME	0.04079	0.4245	28E3	0.10	0.9234
STATE_MA	0.3744	0.2311	28E3	1.62	0.1052
STATE_MI	0.5406	0.2468	28E3	2.19	0.0285
STATE_MN	0.6520	0.3052	28E3	2.14	0.0326
STATE_MS	0.4898	0.3578	28E3	1.37	0.1710
STATE_MO	0.3729	0.2535	28E3	1.47	0.1413
STATE_MT	-0.1723	0.2582	28E3	-0.67	0.5047
STATE_NE	0	.	.	.	.
STATE_NH	0.8805	0.3583	28E3	2.46	0.0140
STATE_NV	0.5138	0.2695	28E3	1.91	0.0566
STATE_NJ	0.6672	0.2204	28E3	3.03	0.0025
STATE_NM	0.4474	0.2345	28E3	1.91	0.0565
STATE_NY	0.5756	0.2085	28E3	2.76	0.0058
STATE_NC	0.3821	0.2670	28E3	1.43	0.1523
STATE_OH	0.6663	0.2078	28E3	3.21	0.0013
STATE_OK	0.2624	0.2188	28E3	1.20	0.2304
STATE_OR	0.5794	0.2186	28E3	2.65	0.0080
STATE_PA	0.5601	0.1969	28E3	2.85	0.0044
STATE_RI	0.4777	0.2744	28E3	1.74	0.0817
STATE_SC	0.4317	0.2369	28E3	1.82	0.0684
STATE_SD	0.1921	0.4055	28E3	0.47	0.6357
STATE_TN	0.6124	0.2032	28E3	3.01	0.0026
STATE_TX	0.4107	0.1986	28E3	2.07	0.0387
STATE_UT	0.7662	0.2634	28E3	2.91	0.0036
STATE_VT	0	.	.	.	.
STATE_VA	0.6144	0.2090	28E3	2.94	0.0033
STATE_WA	0.6772	0.2126	28E3	3.18	0.0014
STATE_WI	0.7196	0.2263	28E3	3.18	0.0015
STATE_WY	-0.1883	0.3295	28E3	-0.57	0.5678
STATE_WV	0.4747	0.2460	28E3	1.93	0.0537

B.5. Model Output for MODEL P_6: the Differential Effect of Natural Disasters on Neighborhood Poverty Rates According to the Intensity of Natural Disasters (Table 5-15 on p. 143)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	-83448.25097510	
1	4	-85979.54642446	0.00120026
2	3	-86029.74142006	.
3	1	-86076.73569375	0.00007551
4	1	-86083.06767728	0.00000528
5	1	-86083.49890578	0.00000015
6	1	-86083.51024740	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.000417	0.000062	6.74	<.0001
TIME	GEO2000	2.004E-6	0	.	.
DISASTER	GEO2000	0.000162	0.000075	2.17	0.0151
POSTTIME	GEO2000	0	.	.	.
Residual		0.004485	0.000036	124.65	<.0001

Fit Statistics

-2 Log Likelihood	-86083.5
AIC (smaller is better)	-85945.5
AICC (smaller is better)	-85945.2
BIC (smaller is better)	-85547.8

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	0.3809	0.01728	2306	22.04	<.0001
TIME	0.002311	0.000208	2331	11.13	<.0001
TIME*INCOME	6.654E-8	0	29E3	Infty	<.0001
DISASTER	0.02618	0.003126	337	8.37	<.0001
DISASTER*INTENS_O	0.04874	0.01425	29E3	3.42	0.0006
POSTTIME	-0.00140	0.000237	303	-5.90	<.0001
INCOME	-3.18E-6	0	29E3	-Infty	<.0001
NEWHOME	-0.02084	0.003079	29E3	-6.77	<.0001
OLDHOME	0.06233	0.001926	29E3	32.37	<.0001
WHITE	-0.2068	0.001936	29E3	-106.81	<.0001

B.5. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
HISPANIC	0.1872	0.003621	29E3	51.71	<.0001
M_POP	-789E-12	0	29E3	-Infty	<.0001
M_INC	-1.63E-6	0	29E3	-Infty	<.0001
M_UEMP	0.001947	0.003610	29E3	0.54	0.5897
R_POP	-0.3238	0.07639	29E3	-4.24	<.0001
NATURAL	0.000137	0.000571	29E3	0.24	0.8101
CBD	0.009684	0.001395	29E3	6.94	<.0001
HIGHWAY	-0.00033	0.000114	29E3	-2.89	0.0038
HUGO	0.02378	0.01274	29E3	1.87	0.0621
ELENA	0.03595	0.02385	29E3	1.51	0.1317
ALICIA	0.000104	0.01117	29E3	0.01	0.9925
GLORIA	-0.00341	0.007340	29E3	-0.47	0.6418
ALLEN	0.1235	0.01514	29E3	8.16	<.0001
STATE_AZ	-0.04728	0.01727	29E3	-2.74	0.0062
STATE_AR	-0.03175	0.01766	29E3	-1.80	0.0722
STATE_CA	-0.05698	0.01735	29E3	-3.28	0.0010
STATE_CO	-0.05037	0.01722	29E3	-2.92	0.0035
STATE_CT	-0.07111	0.01873	29E3	-3.80	0.0001
STATE_DC	-0.1278	0.02757	29E3	-4.64	<.0001
STATE_DE	-0.04575	0.02576	29E3	-1.78	0.0757
STATE_FL	-0.02406	0.01778	29E3	-1.35	0.1761
STATE_GA	-0.00282	0.02001	29E3	-0.14	0.8881
STATE_ID	-0.03483	0.02389	29E3	-1.46	0.1449
STATE_IL	0	.	.	.	.
STATE_IN	-0.04364	0.05501	29E3	-0.79	0.4276
STATE_KY	-0.01942	0.01926	29E3	-1.01	0.3134
STATE_LA	-0.01265	0.02078	29E3	-0.61	0.5428
STATE_MD	-0.05831	0.01822	29E3	-3.20	0.0014
STATE_ME	-0.05292	0.03285	29E3	-1.61	0.1072
STATE_MA	-0.06659	0.01964	29E3	-3.39	0.0007
STATE_MI	-0.06512	0.02121	29E3	-3.07	0.0021
STATE_MN	-0.07032	0.02382	29E3	-2.95	0.0032
STATE_MS	-0.01817	0.03156	29E3	-0.58	0.5647
STATE_MO	-0.05348	0.02149	29E3	-2.49	0.0128
STATE_MT	-0.04362	0.02215	29E3	-1.97	0.0489
STATE_NE	0	.	.	.	.
STATE_NH	-0.05219	0.02880	29E3	-1.81	0.0700
STATE_NV	-0.08190	0.02228	29E3	-3.68	0.0002
STATE_NJ	-0.07175	0.01898	29E3	-3.78	0.0002
STATE_NM	-0.07129	0.02044	29E3	-3.49	0.0005
STATE_NY	-0.07349	0.01831	29E3	-4.01	<.0001
STATE_NC	-0.08675	0.02235	29E3	-3.88	0.0001
STATE_OH	-0.06014	0.01834	29E3	-3.28	0.0010
STATE_OK	-0.03600	0.01915	29E3	-1.88	0.0602
STATE_OR	-0.03406	0.01899	29E3	-1.79	0.0729
STATE_PA	-0.07028	0.01756	29E3	-4.00	<.0001
STATE_RI	-0.04997	0.02246	29E3	-2.23	0.0261
STATE_SC	-0.04449	0.02026	29E3	-2.20	0.0281
STATE_SD	-0.05128	0.03291	29E3	-1.56	0.1192
STATE_TN	-0.01788	0.01813	29E3	-0.99	0.3240
STATE_TX	-0.04199	0.01772	29E3	-2.37	0.0178
STATE_UT	-0.03979	0.02139	29E3	-1.86	0.0629
STATE_VT	0	.	.	.	.
STATE_VA	-0.05958	0.01854	29E3	-3.21	0.0013
STATE_WA	-0.05691	0.01860	29E3	-3.06	0.0022
STATE_WI	-0.07974	0.01955	29E3	-4.08	<.0001
STATE_WY	-0.06894	0.02966	29E3	-2.32	0.0201
STATE_WV	-0.05530	0.02154	29E3	-2.57	0.0102

B.6. Model Output for MODEL D_6: the Differential Effect of Natural Disasters on Neighborhood Racial Diversity According to the Intensity of Natural Disasters (Table 5-16 on p. 146)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	-25223.70103749	
1	2	-28639.53828580	.
2	1	-28957.32717840	0.00063356
3	1	-28991.83747439	0.00007183
4	1	-28995.39689811	0.00000101
5	1	-28995.44393323	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.005453	0.000369	14.77	<.0001
TIME	GEO2000	5.537E-6	0	.	.
DISASTER	GEO2000	0.000071	0.000267	0.26	0.3960
POSTTIME	GEO2000	4.119E-6	2.159E-6	1.91	0.0282
Residual		0.02322	0.000186	125.03	<.0001

Fit Statistics

-2 Log Likelihood	-28995.4
AIC (smaller is better)	-28853.4
AICC (smaller is better)	-28853.1
BIC (smaller is better)	-28444.2

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	0.5674	0.04376	2306	12.97	<.0001
TIME	0.007795	0.000450	2331	17.31	<.0001
TIME*INCOME	1.838E-9	0	29E3	Infty	<.0001
DISASTER	-0.01323	0.006525	337	-2.03	0.0434
DISASTER*INTENS_O	0.2099	0.09506	29E3	2.21	0.0273
POSTTIME	-0.00023	0.000564	303	-0.40	0.6862
INTENS_O*POSTTIME	-0.01654	0.01073	29E3	-1.54	0.1232
INCOME	-7.57E-7	0	29E3	-Infty	<.0001
NEWHOME	0.01593	0.007062	29E3	2.26	0.0241
OLDHOME	0.01148	0.004402	29E3	2.61	0.0091
WHITE	-0.3507	0.004432	29E3	-79.12	<.0001

B.6. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
HISPANIC	0.6526	0.008384	29E3	77.84	<.0001
M_POP	-1.39E-9	0	29E3	-Infty	<.0001
M_INC	-3.92E-7	0	29E3	-Infty	<.0001
M_UEMP	-0.06111	0.008702	29E3	-7.02	<.0001
R_POP	-0.08654	0.1830	29E3	-0.47	0.6363
NATURAL	-0.01030	0.001469	29E3	-7.02	<.0001
CBD	-0.02955	0.003685	29E3	-8.02	<.0001
HIGHWAY	-0.00195	0.000284	29E3	-6.86	<.0001
HUGO	-0.01467	0.03906	29E3	-0.38	0.7071
ELENA	0.01646	0.07120	29E3	0.23	0.8172
ALICIA	0.03888	0.03503	29E3	1.11	0.2670
GLORIA	0.06078	0.02293	29E3	2.65	0.0080
ALLEN	-0.4064	0.04899	29E3	-8.30	<.0001
STATE_AZ	-0.07044	0.04382	29E3	-1.61	0.1080
STATE_AR	-0.07953	0.04475	29E3	-1.78	0.0756
STATE_CA	0.04705	0.04405	29E3	1.07	0.2854
STATE_CO	-0.08669	0.04370	29E3	-1.98	0.0473
STATE_CT	-0.09857	0.04932	29E3	-2.00	0.0457
STATE_DC	-0.1749	0.08712	29E3	-2.01	0.0447
STATE_DE	-0.02343	0.07526	29E3	-0.31	0.7555
STATE_FL	-0.02005	0.04623	29E3	-0.43	0.6645
STATE_GA	0.08749	0.05284	29E3	1.66	0.0978
STATE_ID	-0.1143	0.06565	29E3	-1.74	0.0816
STATE_IL	0	.	.	.	.
STATE_IN	-0.2671	0.1284	29E3	-2.08	0.0375
STATE_KY	-0.1466	0.05007	29E3	-2.93	0.0034
STATE_LA	0.05849	0.05632	29E3	1.04	0.2990
STATE_MD	-0.04941	0.04775	29E3	-1.03	0.3008
STATE_ME	-0.2271	0.09621	29E3	-2.36	0.0183
STATE_MA	-0.1795	0.05327	29E3	-3.37	0.0008
STATE_MI	-0.1004	0.05735	29E3	-1.75	0.0799
STATE_MN	-0.1277	0.07011	29E3	-1.82	0.0686
STATE_MS	0.05658	0.08407	29E3	0.67	0.5010
STATE_MO	-0.1204	0.05880	29E3	-2.05	0.0406
STATE_MT	-0.02407	0.05975	29E3	-0.40	0.6871
STATE_NE	0	.	.	.	.
STATE_NH	-0.2601	0.08270	29E3	-3.15	0.0017
STATE_NV	0.06004	0.06244	29E3	0.96	0.3363
STATE_NJ	-0.1061	0.05083	29E3	-2.09	0.0369
STATE_NM	-0.2235	0.05446	29E3	-4.11	<.0001
STATE_NY	-0.1257	0.04812	29E3	-2.61	0.0090
STATE_NC	0.003829	0.06169	29E3	0.06	0.9505
STATE_OH	-0.1481	0.04806	29E3	-3.08	0.0021
STATE_OK	0.02428	0.05058	29E3	0.48	0.6312
STATE_OR	-0.08530	0.05057	29E3	-1.69	0.0917
STATE_PA	-0.1294	0.04540	29E3	-2.85	0.0044
STATE_RI	-0.2079	0.06347	29E3	-3.28	0.0011
STATE_SC	0.09447	0.05490	29E3	1.72	0.0853
STATE_SD	0.05023	0.09462	29E3	0.53	0.5963
STATE_TN	-0.05944	0.04693	29E3	-1.27	0.2053
STATE_TX	-0.06126	0.04580	29E3	-1.34	0.1810
STATE_UT	-0.1053	0.06067	29E3	-1.74	0.0825
STATE_VT	0	.	.	.	.
STATE_VA	-0.02687	0.04819	29E3	-0.56	0.5770
STATE_WA	-0.03008	0.04919	29E3	-0.61	0.5409
STATE_WI	-0.1695	0.05238	29E3	-3.24	0.0012
STATE_WY	-0.08990	0.07789	29E3	-1.15	0.2485
STATE_WV	-0.1638	0.05718	29E3	-2.86	0.0042

B.7. Model Output for MODEL H_7: the Differential Effects of Natural Disasters on Neighborhood Home Values According to the Neighborhood Income (Table 5-17 on p. 150)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	72938.61350076	
1	4	70767.19850979	.
2	1	70675.80578845	.
3	1	70636.11625669	0.00160311
4	1	70625.88072636	0.00016346
5	1	70624.92730633	0.00000213
6	1	70624.91558618	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.09443	0.006106	15.46	<.0001
TIME	GEO2000	0.000059	6.282E-6	9.43	<.0001
DISASTER	GEO2000	0.03179	0.008246	3.86	<.0001
POSTTIME	GEO2000	0.000030	0.000033	0.92	0.1784
Residual		0.4778	0.003974	120.25	<.0001

Fit Statistics

-2 Log Likelihood	70624.9
AIC (smaller is better)	70770.9
AICC (smaller is better)	70771.2
BIC (smaller is better)	71191.6

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	8.0621	0.1912	2292	42.17	<.0001
TIME	0.04713	0.002015	2304	23.39	<.0001
TIME*INCOME	-1.38E-6	0	27E3	-Infty	<.0001
DISASTER	-0.01780	0.03728	332	-0.48	0.6332
DISASTER*LOWINC	-0.01701	0.05361	27E3	-0.32	0.7511
DISASTER*HIGHINC	-0.3508	0.05437	27E3	-6.45	<.0001
POSTTIME	0.000952	0.002876	279	0.33	0.7410
LOWINC*POSTTIME	-0.01316	0.004669	27E3	-2.82	0.0048
HIGHINC*POSTTIME	0.02774	0.004797	27E3	5.78	<.0001
INCOME	0.000053	0	27E3	Infty	<.0001
NEWHOME	-0.09650	0.03296	27E3	-2.93	0.0034
OLDHOME	-0.2790	0.02085	27E3	-13.38	<.0001
WHITE	0.3089	0.02106	27E3	14.66	<.0001
HISPANIC	-0.5291	0.03973	27E3	-13.32	<.0001
M_POP	9.046E-9	0	27E3	Infty	<.0001
M_INC	0.000010	1.348E-6	27E3	7.60	<.0001
M_UEMP	-0.04358	0.03823	27E3	-1.14	0.2543

B.7. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
R_POP	19.2400	0.8595	27E3	22.39	<.0001
NATURAL	0.02630	0.006381	27E3	4.12	<.0001
CBD	-0.1468	0.01609	27E3	-9.12	<.0001
HIGHWAY	0.001285	0.001252	27E3	1.03	0.3047
HUGO	0.04865	0.1642	27E3	0.30	0.7670
ELENA	-0.3449	0.2984	27E3	-1.16	0.2478
ALICIA	0.1442	0.1504	27E3	0.96	0.3376
GLORIA	0.1777	0.09766	27E3	1.82	0.0688
ALLEN	0.3262	0.2061	27E3	1.58	0.1135
STATE_AZ	0.6682	0.1911	27E3	3.50	0.0005
STATE_AR	0.4430	0.1955	27E3	2.27	0.0234
STATE_CA	0.9044	0.1920	27E3	4.71	<.0001
STATE_CO	0.6829	0.1905	27E3	3.58	0.0003
STATE_CT	0.7310	0.2141	27E3	3.41	0.0006
STATE_DC	0.8808	0.3692	27E3	2.39	0.0171
STATE_DE	0.2521	0.3191	27E3	0.79	0.4296
STATE_FL	0.4093	0.2003	27E3	2.04	0.0410
STATE_GA	0.3822	0.2279	27E3	1.68	0.0935
STATE_ID	0.1983	0.2774	27E3	0.71	0.4748
STATE_IL	0	.	.	.	.
STATE_IN	0.1355	0.5346	27E3	0.25	0.7999
STATE_KY	0.4669	0.2156	27E3	2.17	0.0304
STATE_LA	0.6365	0.2418	27E3	2.63	0.0085
STATE_MD	0.7403	0.2067	27E3	3.58	0.0003
STATE_ME	0.05016	0.4173	27E3	0.12	0.9043
STATE_MA	0.3746	0.2301	27E3	1.63	0.1035
STATE_MI	0.5684	0.2457	27E3	2.31	0.0207
STATE_MN	0.6455	0.3011	27E3	2.14	0.0320
STATE_MS	0.4854	0.3528	27E3	1.38	0.1689
STATE_MO	0.4153	0.2519	27E3	1.65	0.0993
STATE_MT	-0.1613	0.2562	27E3	-0.63	0.5288
STATE_NE	0	.	.	.	.
STATE_NH	0.8936	0.3534	27E3	2.53	0.0115
STATE_NV	0.5141	0.2670	27E3	1.93	0.0542
STATE_NJ	0.6831	0.2199	27E3	3.11	0.0019
STATE_NM	0.4414	0.2333	27E3	1.89	0.0585
STATE_NY	0.5888	0.2088	27E3	2.82	0.0048
STATE_NC	0.4100	0.2650	27E3	1.55	0.1218
STATE_OH	0.6709	0.2076	27E3	3.23	0.0012
STATE_OK	0.3111	0.2228	27E3	1.40	0.1627
STATE_OR	0.5784	0.2178	27E3	2.66	0.0079
STATE_PA	0.5650	0.1970	27E3	2.87	0.0041
STATE_RI	0.4862	0.2717	27E3	1.79	0.0736
STATE_SC	0.4361	0.2355	27E3	1.85	0.0641
STATE_SD	0.2017	0.3988	27E3	0.51	0.6130
STATE_TN	0.6175	0.2031	27E3	3.04	0.0024
STATE_TX	0.4177	0.1987	27E3	2.10	0.0356
STATE_UT	0.8069	0.2612	27E3	3.09	0.0020
STATE_VT	0	.	.	.	.
STATE_VA	0.6141	0.2088	27E3	2.94	0.0033
STATE_WA	0.6795	0.2121	27E3	3.20	0.0014
STATE_WI	0.7214	0.2252	27E3	3.20	0.0014
STATE_WY	-0.1710	0.3252	27E3	-0.53	0.5990

B.8. Model Output for MODEL P_7: the Differential Effects of Natural Disasters on Neighborhood Poverty Rates According to the Neighborhood Income (Table 5-18 on p. 154)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	-83076.69351545	
1	4	-85585.30318724	.
2	2	-85612.53973248	0.00010212
3	1	-85621.66039209	0.00002176
4	1	-85623.54611227	0.00000222
5	1	-85623.72228271	0.00000003
6	1	-85623.72442766	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.000425	0.000061	6.92	<.0001
TIME	GEO2000	1.917E-6	0	.	.
DISASTER	GEO2000	0.000277	0.000089	3.11	0.0010
POSTTIME	GEO2000	0	.	.	.
Residual		0.004415	0.000036	123.94	<.0001

Fit Statistics

-2 Log Likelihood	-85623.7
AIC (smaller is better)	-85483.7
AICC (smaller is better)	-85483.4
BIC (smaller is better)	-85080.3

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	0.3768	0.01756	2301	21.46	<.0001
TIME	0.002437	0.000208	2321	11.72	<.0001
TIME*INCOME	6.958E-8	0	29E3	Infty	<.0001
DISASTER	0.01156	0.003279	337	3.53	0.0005
DISASTER*LOWINC	0.06146	0.002517	29E3	24.42	<.0001
DISASTER*HIGHINC	0.04758	0.002686	29E3	17.71	<.0001
POSTTIME	-0.00203	0.000233	306	-8.72	<.0001
INCOME	-3.35E-6	0	29E3	-Infty	<.0001
NEWHOME	-0.02217	0.003077	29E3	-7.20	<.0001
OLDHOME	0.06202	0.001925	29E3	32.22	<.0001

B.8. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
WHITE	-0.2005	0.001941	29E3	-103.26	<.0001
HISPANIC	0.1780	0.003607	29E3	49.34	<.0001
M_POP	-644E-12	0	29E3	-Infty	<.0001
M_INC	-1.63E-6	0	29E3	-Infty	<.0001
M_UEMP	0.000706	0.003603	29E3	0.20	0.8446
R_POP	-0.2578	0.07656	29E3	-3.37	0.0008
NATURAL	0.000147	0.000571	29E3	0.26	0.7968
CBD	0.009244	0.001400	29E3	6.60	<.0001
HIGHWAY	-0.00031	0.000114	29E3	-2.68	0.0074
HUGO	0.02557	0.01281	29E3	2.00	0.0460
ELENA	0.03879	0.02401	29E3	1.62	0.1062
ALICIA	0.001724	0.01126	29E3	0.15	0.8783
GLORIA	-0.00356	0.007393	29E3	-0.48	0.6302
ALLEN	0.1282	0.01522	29E3	8.42	<.0001
STATE_AZ	-0.04519	0.01755	29E3	-2.57	0.0100
STATE_AR	-0.03382	0.01798	29E3	-1.88	0.0600
STATE_CA	-0.05500	0.01763	29E3	-3.12	0.0018
STATE_CO	-0.04886	0.01750	29E3	-2.79	0.0053
STATE_CT	-0.07119	0.01901	29E3	-3.74	0.0002
STATE_DC	-0.1234	0.02789	29E3	-4.42	<.0001
STATE_DE	-0.04527	0.02602	29E3	-1.74	0.0819
STATE_FL	-0.02347	0.01806	29E3	-1.30	0.1938
STATE_GA	-0.00176	0.02024	29E3	-0.09	0.9307
STATE_ID	-0.03551	0.02408	29E3	-1.47	0.1403
STATE_IL	0	.	.	.	.
STATE_IN	-0.04483	0.05454	29E3	-0.82	0.4111
STATE_KY	-0.01885	0.01952	29E3	-0.97	0.3341
STATE_LA	-0.01272	0.02106	29E3	-0.60	0.5461
STATE_MD	-0.05704	0.01850	29E3	-3.08	0.0020
STATE_ME	-0.05385	0.03305	29E3	-1.63	0.1032
STATE_MA	-0.06596	0.01992	29E3	-3.31	0.0009
STATE_MI	-0.06528	0.02145	29E3	-3.04	0.0023
STATE_MN	-0.06911	0.02414	29E3	-2.86	0.0042
STATE_MS	-0.01425	0.03167	29E3	-0.45	0.6528
STATE_MO	-0.05319	0.02184	29E3	-2.44	0.0149
STATE_MT	-0.04520	0.02236	29E3	-2.02	0.0432
STATE_NE	0	.	.	.	.
STATE_NH	-0.05236	0.02903	29E3	-1.80	0.0713
STATE_NV	-0.07971	0.02253	29E3	-3.54	0.0004
STATE_NJ	-0.07269	0.01926	29E3	-3.77	0.0002
STATE_NM	-0.06766	0.02068	29E3	-3.27	0.0011
STATE_NY	-0.07341	0.01861	29E3	-3.94	<.0001
STATE_NC	-0.08712	0.02268	29E3	-3.84	0.0001
STATE_OH	-0.06018	0.01862	29E3	-3.23	0.0012
STATE_OK	-0.04003	0.01962	29E3	-2.04	0.0413
STATE_OR	-0.03387	0.01927	29E3	-1.76	0.0788
STATE_PA	-0.07014	0.01784	29E3	-3.93	<.0001
STATE_RI	-0.05017	0.02272	29E3	-2.21	0.0272
STATE_SC	-0.04297	0.02052	29E3	-2.09	0.0363
STATE_SD	-0.05331	0.03305	29E3	-1.61	0.1067
STATE_TN	-0.01735	0.01840	29E3	-0.94	0.3458
STATE_TX	-0.04100	0.01800	29E3	-2.28	0.0227
STATE_UT	-0.04066	0.02172	29E3	-1.87	0.0612
STATE_VT	0	.	.	.	.
STATE_VA	-0.05874	0.01881	29E3	-3.12	0.0018
STATE_WA	-0.05638	0.01888	29E3	-2.99	0.0028
STATE_WI	-0.08018	0.01980	29E3	-4.05	<.0001
STATE_WY	-0.07120	0.02970	29E3	-2.40	0.0165
STATE_WV	-0.05701	0.02174	29E3	-2.62	0.0088

B.9. Model Output for MODEL D_7: the Differential Effects of Natural Disasters on Neighborhood Racial Diversity According to the Neighborhood Income (Table 5-19 on p. 158)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	-24838.71878609	
1	2	-28412.30067294	0.00208189
2	1	-28531.85702214	0.00066602
3	1	-28567.75604636	0.00007779
4	1	-28571.57025308	0.00000116
5	1	-28571.62362716	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.005618	0.000377	14.90	<.0001
TIME	GEO2000	5.333E-6	0	.	.
DISASTER	GEO2000	0.000204	0.000270	0.76	0.2244
POSTTIME	GEO2000	2.832E-6	1.97E-6	1.44	0.0753
Residual		0.02328	0.000187	124.29	<.0001

Fit Statistics

-2 Log Likelihood	-28571.6
AIC (smaller is better)	-28425.6
AICC (smaller is better)	-28425.3
BIC (smaller is better)	-28005.0

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	0.5736	0.04479	2301	12.81	<.0001
TIME	0.007626	0.000453	2321	16.84	<.0001
TIME*INCOME	-3.05E-9	0	29E3	-Infty	<.0001
DISASTER	0.002344	0.007478	337	0.31	0.7541
DISASTER*LOWINC	-0.02810	0.01129	29E3	-2.49	0.0129
DISASTER*HIGHINC	-0.04214	0.01187	29E3	-3.55	0.0004
POSTTIME	-0.00059	0.000648	305	-0.91	0.3626
LOWINC*POSTTIME	-0.00116	0.000997	29E3	-1.16	0.2467
HIGHINC*POSTTIME	0.003183	0.001054	29E3	3.02	0.0025
INCOME	-6.92E-7	0	29E3	-Infty	<.0001
NEWHOME	0.01842	0.007121	29E3	2.59	0.0097

B.9. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
OLDHOME	0.01112	0.004440	29E3	2.50	0.0123
WHITE	-0.3520	0.004485	29E3	-78.48	<.0001
HISPANIC	0.6576	0.008433	29E3	77.98	<.0001
M_POP	-1.44E-9	0	29E3	-Infty	<.0001
M_INC	-2.16E-7	0	29E3	-Infty	<.0001
M_UEMP	-0.06091	0.008778	29E3	-6.94	<.0001
R_POP	-0.08160	0.1852	29E3	-0.44	0.6595
NATURAL	-0.01053	0.001485	29E3	-7.09	<.0001
CBD	-0.03041	0.003730	29E3	-8.15	<.0001
HIGHWAY	-0.00195	0.000286	29E3	-6.80	<.0001
HUGO	-0.01317	0.03956	29E3	-0.33	0.7391
ELENA	0.01535	0.07204	29E3	0.21	0.8313
ALICIA	0.03618	0.03550	29E3	1.02	0.3081
GLORIA	0.05731	0.02336	29E3	2.45	0.0142
ALLEN	-0.4026	0.04963	29E3	-8.11	<.0001
STATE_AZ	-0.07615	0.04484	29E3	-1.70	0.0895
STATE_AR	-0.08583	0.04586	29E3	-1.87	0.0612
STATE_CA	0.04175	0.04507	29E3	0.93	0.3542
STATE_CO	-0.09291	0.04472	29E3	-2.08	0.0377
STATE_CT	-0.1008	0.05042	29E3	-2.00	0.0455
STATE_DC	-0.1869	0.08860	29E3	-2.11	0.0349
STATE_DE	-0.02925	0.07650	29E3	-0.38	0.7023
STATE_FL	-0.02670	0.04725	29E3	-0.57	0.5720
STATE_GA	0.08151	0.05383	29E3	1.51	0.1300
STATE_ID	-0.1209	0.06667	29E3	-1.81	0.0697
STATE_IL	0	.	.	.	.
STATE_IN	-0.2724	0.1290	29E3	-2.11	0.0347
STATE_KY	-0.1536	0.05107	29E3	-3.01	0.0026
STATE_LA	0.05516	0.05740	29E3	0.96	0.3366
STATE_MD	-0.05712	0.04879	29E3	-1.17	0.2417
STATE_ME	-0.2321	0.09759	29E3	-2.38	0.0174
STATE_MA	-0.1827	0.05440	29E3	-3.36	0.0008
STATE_MI	-0.1042	0.05847	29E3	-1.78	0.0747
STATE_MN	-0.1343	0.07141	29E3	-1.88	0.0599
STATE_MS	0.04632	0.08511	29E3	0.54	0.5863
STATE_MO	-0.1275	0.05998	29E3	-2.12	0.0336
STATE_MT	-0.02872	0.06075	29E3	-0.47	0.6363
STATE_NE	0	.	.	.	.
STATE_NH	-0.2632	0.08390	29E3	-3.14	0.0017
STATE_NV	0.05470	0.06351	29E3	0.86	0.3891
STATE_NJ	-0.1104	0.05194	29E3	-2.13	0.0336
STATE_NM	-0.2305	0.05545	29E3	-4.16	<.0001
STATE_NY	-0.1294	0.04930	29E3	-2.62	0.0087
STATE_NC	-0.01169	0.06288	29E3	-0.19	0.8525
STATE_OH	-0.1560	0.04909	29E3	-3.18	0.0015
STATE_OK	0.01756	0.05255	29E3	0.33	0.7383
STATE_OR	-0.09132	0.05161	29E3	-1.77	0.0768
STATE_PA	-0.1362	0.04642	29E3	-2.93	0.0034
STATE_RI	-0.2115	0.06463	29E3	-3.27	0.0011
STATE_SC	0.08883	0.05595	29E3	1.59	0.1124
STATE_SD	0.04557	0.09608	29E3	0.47	0.6353
STATE_TN	-0.06595	0.04793	29E3	-1.38	0.1688
STATE_TX	-0.06741	0.04682	29E3	-1.44	0.1499
STATE_UT	-0.1115	0.06185	29E3	-1.80	0.0715
STATE_VT	0	.	.	.	.
STATE_VA	-0.03517	0.04920	29E3	-0.71	0.4747
STATE_WA	-0.03695	0.05023	29E3	-0.74	0.4620
STATE_WI	-0.1769	0.05341	29E3	-3.31	0.0009
STATE_WY	-0.09643	0.07883	29E3	-1.22	0.2213
STATE_WV	-0.1709	0.05817	29E3	-2.94	0.0033

B.10. Model Output for MODEL H_8: the Differential Effects of Natural Disasters on Neighborhood Home Values According to the Role of Municipality (Table 5-20 on p. 162)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	74231.43816456	
1	4	72117.11480755	.
2	1	71966.84759228	.
3	1	71879.57606837	0.00543321
4	1	71841.00370432	.
5	1	71831.36887140	0.00013817
6	1	71830.53324559	0.00000154
7	1	71830.52444437	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.1008	0.006445	15.64	<.0001
TIME	GEO2000	0.000064	6.578E-6	9.75	<.0001
DISASTER	GEO2000	0.01817	0.007441	2.44	0.0073
POSTTIME	GEO2000	0.000025	0.000036	0.69	0.2465
Residual		0.4817	0.003992	120.69	<.0001

Fit Statistics

-2 Log Likelihood	71830.5
AIC (smaller is better)	71972.5
AICC (smaller is better)	71972.8
BIC (smaller is better)	72381.8

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	8.0789	0.1913	2296	42.23	<.0001
TIME	0.04934	0.002014	2313	24.50	<.0001
TIME*INCOME	-1.32E-6	0	28E3	-Infty	<.0001
DISASTER	-0.1181	0.03593	331	-3.29	0.0011
DISASTER*CEN_CITY	0.2821	0.06060	28E3	4.65	<.0001
POSTTIME	0.003321	0.002799	278	1.19	0.2365
CEN_CITY*POSTTIME	-0.00410	0.004565	28E3	-0.90	0.3696
INCOME	0.000051	0	28E3	Infty	<.0001
NEWHOME	-0.09500	0.03288	28E3	-2.89	0.0039
OLDHOME	-0.2801	0.02076	28E3	-13.49	<.0001
WHITE	0.3187	0.02093	28E3	15.23	<.0001
HISPANIC	-0.5682	0.03967	28E3	-14.32	<.0001
M_POP	1.069E-8	0	28E3	Infty	<.0001
M_INC	8.407E-6	1.337E-6	28E3	6.29	<.0001
M_UEMP	-0.05412	0.03869	28E3	-1.40	0.1619
R_POP	19.6605	0.8597	28E3	22.87	<.0001

B.10. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
NATURAL	0.02743	0.006480	28E3	4.23	<.0001
CBD	-0.1508	0.01630	28E3	-9.25	<.0001
HIGHWAY	0.001472	0.001266	28E3	1.16	0.2447
HUGO	0.06303	0.1684	28E3	0.37	0.7082
ELENA	-0.3487	0.3053	28E3	-1.14	0.2534
ALICIA	0.1502	0.1541	28E3	0.97	0.3300
GLORIA	0.1820	0.09960	28E3	1.83	0.0676
ALLEN	0.3777	0.2119	28E3	1.78	0.0747
STATE_AZ	0.6727	0.1913	28E3	3.52	0.0004
STATE_AR	0.4213	0.1954	28E3	2.16	0.0311
STATE_CA	0.9005	0.1922	28E3	4.68	<.0001
STATE_CO	0.6947	0.1907	28E3	3.64	0.0003
STATE_CT	0.7209	0.2151	28E3	3.35	0.0008
STATE_DC	0.8974	0.3780	28E3	2.37	0.0176
STATE_DE	0.2586	0.3247	28E3	0.80	0.4261
STATE_FL	0.4079	0.2012	28E3	2.03	0.0426
STATE_GA	0.3753	0.2300	28E3	1.63	0.1027
STATE_ID	0.1925	0.2820	28E3	0.68	0.4948
STATE_IL	0	.	.	.	.
STATE_IN	0.1334	0.5442	28E3	0.25	0.8064
STATE_KY	0.4555	0.2171	28E3	2.10	0.0359
STATE_LA	0.6496	0.2443	28E3	2.66	0.0079
STATE_MD	0.7661	0.2078	28E3	3.69	0.0002
STATE_ME	0.05369	0.4250	28E3	0.13	0.8995
STATE_MA	0.3822	0.2319	28E3	1.65	0.0993
STATE_MI	0.5462	0.2480	28E3	2.20	0.0276
STATE_MN	0.6582	0.3068	28E3	2.15	0.0319
STATE_MS	0.5011	0.3591	28E3	1.40	0.1629
STATE_MO	0.3808	0.2547	28E3	1.49	0.1349
STATE_MT	-0.1748	0.2595	28E3	-0.67	0.5004
STATE_NE	0	.	.	.	.
STATE_NH	0.8890	0.3592	28E3	2.47	0.0133
STATE_NV	0.5101	0.2708	28E3	1.88	0.0597
STATE_NJ	0.6769	0.2214	28E3	3.06	0.0022
STATE_NM	0.4473	0.2357	28E3	1.90	0.0577
STATE_NY	0.5807	0.2094	28E3	2.77	0.0056
STATE_NC	0.3998	0.2678	28E3	1.49	0.1355
STATE_OH	0.6740	0.2088	28E3	3.23	0.0012
STATE_OK	0.2668	0.2198	28E3	1.21	0.2247
STATE_OR	0.5815	0.2196	28E3	2.65	0.0081
STATE_PA	0.5665	0.1977	28E3	2.87	0.0042
STATE_RI	0.4950	0.2754	28E3	1.80	0.0723
STATE_SC	0.4309	0.2380	28E3	1.81	0.0703
STATE_SD	0.1926	0.4077	28E3	0.47	0.6366
STATE_TN	0.6162	0.2041	28E3	3.02	0.0025
STATE_TX	0.4164	0.1995	28E3	2.09	0.0369
STATE_UT	0.7684	0.2647	28E3	2.90	0.0037
STATE_VT	0	.	.	.	.
STATE_VA	0.6233	0.2099	28E3	2.97	0.0030
STATE_WA	0.6781	0.2136	28E3	3.17	0.0015
STATE_WI	0.7293	0.2274	28E3	3.21	0.0013
STATE_WY	-0.1860	0.3315	28E3	-0.56	0.5747
STATE_WV	0.4793	0.2472	28E3	1.94	0.0525

B.11. Model Output for MODEL P_8: the Differential Effects of Natural Disasters on Neighborhood Poverty Rates According to the Role of Municipality (Table 5-21on p. 166)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	-83117.35164823	
1	4	-85639.22035155	.
2	1	-85747.35928051	0.00035176
3	1	-85778.97332208	0.00006329
4	2	-85784.23191850	0.00000236
5	1	-85784.41235033	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.000405	0.000061	6.67	<.0001
TIME	GEO2000	2.045E-6	0	.	.
DISASTER	GEO2000	0.000085	0.000074	1.15	0.1242
POSTTIME	GEO2000	0	.	.	.
Residual		0.004553	0.000036	124.88	<.0001

Fit Statistics

-2 Log Likelihood	-85784.4
AIC (smaller is better)	-85646.4
AICC (smaller is better)	-85646.1
BIC (smaller is better)	-85248.7

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	0.3817	0.01734	2306	22.01	<.0001
TIME	0.002325	0.000209	2331	11.12	<.0001
TIME*INCOME	6.607E-8	0	29E3	Infty	<.0001
DISASTER	0.03514	0.003264	337	10.77	<.0001
DISASTER*CEN_CITY	-0.01742	0.005015	29E3	-3.47	0.0005
POSTTIME	-0.00173	0.000235	305	-7.39	<.0001
INCOME	-3.23E-6	0	29E3	-Infty	<.0001
NEWHOME	-0.02140	0.003098	29E3	-6.91	<.0001
OLDHOME	0.06121	0.001933	29E3	31.67	<.0001
WHITE	-0.2071	0.001945	29E3	-106.48	<.0001
HISPANIC	0.1885	0.003622	29E3	52.04	<.0001

B.11. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
M_POP	-742E-12	0	29E3	-Infty	<.0001
M_INC	-1.64E-6	0	29E3	-Infty	<.0001
M_UEMP	0.001009	0.003627	29E3	0.28	0.7808
R_POP	-0.2795	0.07662	29E3	-3.65	0.0003
NATURAL	0.000094	0.000573	29E3	0.16	0.8697
CBD	0.009185	0.001396	29E3	6.58	<.0001
HIGHWAY	-0.00032	0.000114	29E3	-2.77	0.0056
HUGO	0.02286	0.01268	29E3	1.80	0.0714
ELENA	0.03394	0.02373	29E3	1.43	0.1526
ALICIA	0.001207	0.01110	29E3	0.11	0.9134
GLORIA	-0.00430	0.007289	29E3	-0.59	0.5554
ALLEN	0.1253	0.01501	29E3	8.35	<.0001
STATE_AZ	-0.04628	0.01733	29E3	-2.67	0.0076
STATE_AR	-0.03113	0.01772	29E3	-1.76	0.0790
STATE_CA	-0.05598	0.01741	29E3	-3.22	0.0013
STATE_CO	-0.04938	0.01728	29E3	-2.86	0.0043
STATE_CT	-0.06846	0.01877	29E3	-3.65	0.0003
STATE_DC	-0.1272	0.02741	29E3	-4.64	<.0001
STATE_DE	-0.04531	0.02568	29E3	-1.76	0.0777
STATE_FL	-0.02300	0.01782	29E3	-1.29	0.1968
STATE_GA	-0.00223	0.02004	29E3	-0.11	0.9113
STATE_ID	-0.03459	0.02389	29E3	-1.45	0.1476
STATE_IL	0	.	.	.	.
STATE_IN	-0.04230	0.05529	29E3	-0.77	0.4443
STATE_KY	-0.01861	0.01930	29E3	-0.96	0.3350
STATE_LA	-0.01135	0.02080	29E3	-0.55	0.5853
STATE_MD	-0.05760	0.01826	29E3	-3.15	0.0016
STATE_ME	-0.05299	0.03276	29E3	-1.62	0.1057
STATE_MA	-0.06489	0.01965	29E3	-3.30	0.0010
STATE_MI	-0.06396	0.02123	29E3	-3.01	0.0026
STATE_MN	-0.06887	0.02376	29E3	-2.90	0.0038
STATE_MS	-0.01862	0.03156	29E3	-0.59	0.5551
STATE_MO	-0.05322	0.02149	29E3	-2.48	0.0133
STATE_MT	-0.04324	0.02217	29E3	-1.95	0.0512
STATE_NE	0	.	.	.	.
STATE_NH	-0.05106	0.02872	29E3	-1.78	0.0755
STATE_NV	-0.08030	0.02225	29E3	-3.61	0.0003
STATE_NJ	-0.07113	0.01900	29E3	-3.74	0.0002
STATE_NM	-0.07080	0.02046	29E3	-3.46	0.0005
STATE_NY	-0.07237	0.01835	29E3	-3.94	<.0001
STATE_NC	-0.08691	0.02234	29E3	-3.89	0.0001
STATE_OH	-0.05932	0.01838	29E3	-3.23	0.0013
STATE_OK	-0.03508	0.01918	29E3	-1.83	0.0674
STATE_OR	-0.03332	0.01902	29E3	-1.75	0.0798
STATE_PA	-0.06922	0.01761	29E3	-3.93	<.0001
STATE_RI	-0.04858	0.02243	29E3	-2.17	0.0303
STATE_SC	-0.04304	0.02028	29E3	-2.12	0.0338
STATE_SD	-0.05149	0.03285	29E3	-1.57	0.1170
STATE_TN	-0.01679	0.01818	29E3	-0.92	0.3557
STATE_TX	-0.04156	0.01776	29E3	-2.34	0.0193
STATE_UT	-0.03901	0.02137	29E3	-1.83	0.0679
STATE_VT	0	.	.	.	.
STATE_VA	-0.05886	0.01858	29E3	-3.17	0.0015
STATE_WA	-0.05574	0.01863	29E3	-2.99	0.0028
STATE_WI	-0.07886	0.01957	29E3	-4.03	<.0001
STATE_WY	-0.06979	0.02970	29E3	-2.35	0.0188
STATE_WV	-0.05486	0.02157	29E3	-2.54	0.0110

B.12. Model Output for MODEL D_8: the Differential Effects of Natural Disasters on Neighborhood Racial Diversity According to the Role of Municipality(Table 5-22 on p. 169)

The Mixed Procedure

Iteration History

Iteration	Evaluations	-2 Log Like	Criterion
0	1	-25209.72065875	
1	2	-28792.52253215	0.00201820
2	1	-28909.86321140	0.00063834
3	1	-28944.71143123	0.00007376
4	1	-28948.37341775	0.00000107
5	1	-28948.42323507	0.00000000

Convergence criteria met.

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	GEO2000	0.005443	0.000369	14.76	<.0001
TIME	GEO2000	5.442E-6	0	.	.
DISASTER	GEO2000	0.000271	0.000275	0.98	0.1623
POSTTIME	GEO2000	2.942E-6	2.024E-6	1.45	0.0731
Residual		0.02331	0.000186	125.18	<.0001

Fit Statistics

-2 Log Likelihood	-28948.4
AIC (smaller is better)	-28806.4
AICC (smaller is better)	-28806.1
BIC (smaller is better)	-28397.2

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
Intercept	0.5660	0.04375	2306	12.94	<.0001
TIME	0.007777	0.000453	2331	17.16	<.0001
TIME*INCOME	1.893E-9	0	29E3	Infty	<.0001
DISASTER	-0.00741	0.007494	337	-0.99	0.3236
DISASTER*CEN_CITY	-0.00931	0.01200	29E3	-0.78	0.4381
POSTTIME	-0.00026	0.000637	304	-0.40	0.6864
CEN_CITY*POSTTIME	-0.00085	0.001053	29E3	-0.80	0.4210
INCOME	-7.67E-7	0	29E3	-Infty	<.0001
NEWHOME	0.01686	0.007068	29E3	2.39	0.0171
OLDHOME	0.01293	0.004396	29E3	2.94	0.0033
WHITE	-0.3496	0.004430	29E3	-78.92	<.0001

B.12. Continued

The Mixed Procedure

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|
HISPANIC	0.6484	0.008344	29E3	77.70	<.0001
M_POP	-1.31E-9	0	29E3	-Infty	<.0001
M_INC	-3.72E-7	0	29E3	-Infty	<.0001
M_UEMP	-0.06111	0.008708	29E3	-7.02	<.0001
R_POP	-0.08298	0.1829	29E3	-0.45	0.6500
NATURAL	-0.01041	0.001470	29E3	-7.08	<.0001
CBD	-0.02980	0.003685	29E3	-8.09	<.0001
HIGHWAY	-0.00192	0.000284	29E3	-6.76	<.0001
HUGO	-0.01325	0.03904	29E3	-0.34	0.7344
ELENA	0.01514	0.07115	29E3	0.21	0.8315
ALICIA	0.03769	0.03501	29E3	1.08	0.2816
GLORIA	0.05978	0.02291	29E3	2.61	0.0091
ALLEN	-0.4017	0.04893	29E3	-8.21	<.0001
STATE_AZ	-0.06928	0.04381	29E3	-1.58	0.1138
STATE_AR	-0.07940	0.04474	29E3	-1.77	0.0760
STATE_CA	0.04805	0.04404	29E3	1.09	0.2752
STATE_CO	-0.08606	0.04369	29E3	-1.97	0.0489
STATE_CT	-0.09605	0.04930	29E3	-1.95	0.0514
STATE_DC	-0.1752	0.08707	29E3	-2.01	0.0441
STATE_DE	-0.02370	0.07523	29E3	-0.32	0.7527
STATE_FL	-0.01962	0.04621	29E3	-0.42	0.6712
STATE_GA	0.08771	0.05282	29E3	1.66	0.0968
STATE_ID	-0.1142	0.06559	29E3	-1.74	0.0818
STATE_IL	0	.	.	.	.
STATE_IN	-0.2674	0.1282	29E3	-2.08	0.0371
STATE_KY	-0.1470	0.05005	29E3	-2.94	0.0033
STATE_LA	0.05896	0.05628	29E3	1.05	0.2950
STATE_MD	-0.05013	0.04774	29E3	-1.05	0.2936
STATE_ME	-0.2278	0.09618	29E3	-2.37	0.0179
STATE_MA	-0.1788	0.05326	29E3	-3.36	0.0008
STATE_MI	-0.1007	0.05732	29E3	-1.76	0.0790
STATE_MN	-0.1283	0.07007	29E3	-1.83	0.0672
STATE_MS	0.05521	0.08400	29E3	0.66	0.5111
STATE_MO	-0.1206	0.05877	29E3	-2.05	0.0401
STATE_MT	-0.02382	0.05972	29E3	-0.40	0.6900
STATE_NE	0	.	.	.	.
STATE_NH	-0.2607	0.08268	29E3	-3.15	0.0016
STATE_NV	0.06106	0.06240	29E3	0.98	0.3279
STATE_NJ	-0.1070	0.05081	29E3	-2.11	0.0353
STATE_NM	-0.2211	0.05443	29E3	-4.06	<.0001
STATE_NY	-0.1267	0.04810	29E3	-2.63	0.0085
STATE_NC	0.001352	0.06168	29E3	0.02	0.9825
STATE_OH	-0.1488	0.04804	29E3	-3.10	0.0020
STATE_OK	0.02444	0.05056	29E3	0.48	0.6288
STATE_OR	-0.08522	0.05055	29E3	-1.69	0.0918
STATE_PA	-0.1302	0.04539	29E3	-2.87	0.0041
STATE_RI	-0.2076	0.06344	29E3	-3.27	0.0011
STATE_SC	0.09529	0.05488	29E3	1.74	0.0825
STATE_SD	0.05079	0.09475	29E3	0.54	0.5919
STATE_TN	-0.05958	0.04691	29E3	-1.27	0.2041
STATE_TX	-0.06038	0.04579	29E3	-1.32	0.1873
STATE_UT	-0.1049	0.06064	29E3	-1.73	0.0837
STATE_VT	0	.	.	.	.
STATE_VA	-0.02736	0.04817	29E3	-0.57	0.5702
STATE_WA	-0.02978	0.04917	29E3	-0.61	0.5448
STATE_WI	-0.1701	0.05236	29E3	-3.25	0.0012
STATE_WY	-0.08976	0.07780	29E3	-1.15	0.2487
STATE_WV	-0.1649	0.05715	29E3	-2.89	0.0039

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